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Performance on Well and Ill-Structured Problems in University Physics: The role of Instruction in Cooperative Learning

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Performance on Well and Ill-Structured Problems in University Physics: The role of Instruction in Cooperative Learning

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by

Javier Alejandro Pulgar

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Abstract

Performance on Well and Ill-Structured Problems in University Physics: The role of Instruction in Cooperative Learning

by

Javier Alejandro Pulgar

In this study, I explore the learning opportunities that emerge from ill-structured activities in a university physics course and how collaboration enables performance under different teaching conditions. The study was conducted over two months on three sections of an introductory physics course in a University in Northern Chile. Each section utilized a different variety of teaching strategies and combinations of problems (well and ill-structured) for assessing content on the day of data collection, students were asked to work in groups and ill-structured activity in physics. I gathered audio of students' discussion in four groups for a total of 26 participants, and I collected the generated problems from the whole sample. From the audio, I explored the emergent processes students engaged while solving the problems. Student generated activities were coded to investigate combinations of concepts and problem characteristics, which were later combined into a measure of problem elaboration. Later, I explored students' social networks to determine how different instructional strategies led to different social configurations and their differences in academic performance. For this, I collected data on students' performance on a physics test designed with well-structured problems and problem elaboration, and I asked students to respond to an on-line peer-nomination survey related to their social interactions engaged for information seeking to solve problems. I tested the effect of different network structures over academic performance on both types of activities by setting statistical linear models.

Generating problems is an opportunity for students to propose ideas and make decisions regarding the content and the contextual details to introduce into their problems, as well as to engage in problem solving strategies. The combination of concepts and attributes for problem elaboration showed students' familiarity with particular portions of the content and characteristics, with differences across sections. Finally, students who actively sought out information from multiple peers were less likely to achieve good performance on well-structured problems, whereas for ill-structured problems, this effect depended on the features of the learning environment enacted in each section. These results suggest that teaching and instructional strategies have a key role in the way cooperation lead to good performance.

Contents

Chapter 1

Introduction

Thinking of education in the 21st Century demands combining principles of creativity and collaboration into the classroom. Contemporary life and work strongly rely on our ability to develop social relationships for support, but also for learning and accessing information and developing new and better ideas (Borgatti and Cross, 2003; Vygotsky, 1978). This is especially important in developed countries that have shifted their efforts for economic growth from the industrial endeavors towards a knowledge-based economy (Sawyer, 2006a). For these reasons, collaboration and creativity have been defined as key competencies for life and work in the 21st century (Pellegrino and Hilton, 2003). Focusing on the production of knowledge is an invitation to think of education as an opportunity to train students into the appropriate skills for collaboration and creativity, a set of skills rarely addressed for such innovative purposes in traditional education (Sawyer, 2006a).

In the context of physics education, scholars have studied collaboration in university classrooms and focused on the benefits of groups over individual performance (Heller et al., 1992), the ways in which teams are effective (Heller and Hollabaugh, 1992; Harlow et al., 2016), and how do students learn in teams while discussing physics ideas

(Leinonen et al., 2017; Buteler and Coleoni, 2016). Even though creativity has not been included as a key outcome in physics classrooms in higher education, through the focus on how students learn physics, scholars have implicitly addressed individual creativity, or the process through which students are building logical connections between pre-existing and new knowledge (Kaufman and Beghetto, 2009), a mechanism that enables individuals' novel and effective understandings of the content. The link between individual learning and collaboration emerged from Vygotsky (1978) and his zone of proximal development (ZPD); yet, besides the work of Heller and Hollabaugh (1992), researchers in this field have not addressed the effects of collaboration on learning across different types of tasks.

Physics education research traditionally has focused intensively on well-structured learning activities, such as mathematical problems, that provide little room for creativity due to its close-ended nature (Jonassen, 2000), and are more appropriate for individual performance (Steiner, 1966), rather than group efforts. This evidence motivated me to reflect on alternative tasks that would encourage socialization of information for collective learning, and would enable processes associated with idea-generation. For such purpose, this work is grounded in the use of ill-structured problems, which consist of open-ended activities that demand higher levels of creative thinking compared to well-structured problems (Heller and Hollabaugh, 1992; Fortus, 2008). Designing physics curriculum upon more creative tasks responds directly to need of developing the appropriate skills for contemporary life and work. One of the goals of this study is to explore collective processes for solving ill-structured problems, along with a deep analysis of students' solutions through the identification of unique characteristics and use of physics ideas.

Creativity and social network literature provide interesting evidence to understand the different individual and social mechanisms that ease collective learning and the emergence of good ideas in professional contexts (Burt, 2004; Rhee and Leonardi, 2003). This work is an attempt to explore whether students in a physics course would take advantage of such mechanism across different teaching and learning strategies enacted in three parallel sections at the university. For such purpose, I investigated students' social networks from three sections in an introductory physics course, and determined the social structures that facilitate good performance on well-structured physics problems (e.g., textbook problems), and creative tasks defined as ill-structured (Jonassen, 2000), which consist of student groups generating physics problems for high school students. Through this analysis, I explored whether good performance on both types of problems is predicted by mechanisms associated with creativity and innovation, such as creative combinations (Burt, 2004) or interrogation logic (Rhee and Leonardi, 2003). In addition, I tested the effects of different instructional strategies on performance, and whether the effect of social structures responded differently depending on the learning environment.

The evidence shown in this work should enable a deeper discussion of the ways in which instruction might take advantage of collaboration for creativity, taking into account the role of the instructor and learning activities, as well as the importance of students' social skills for effective communication.

Chapter 2

Literature Review

The literature review presented here provides a deep description of research evidence on three important fields that outline the research goals of this study: A. Problem solving in physics education research; B. Social Network Analysis (SNA) in education; and C. Group creativity and social learning. Because this study aims to present an alternative mechanism to introduce creativity in physics classrooms, it is important to address the relevant research evidence on physics problem solving in order to identify need for the innovation with ill-structured problems for creativity and learning. Moreover, the methodological lens of analysis that ease the understanding of classroom as complex social system comes from the field of social networks, and particularly from studies conducted in education that highlight the importance of social interactions in students' learning experience, as well as the organizational features that enable different types of social relationships. This prior research suggests methodological tools for data collection and interpretation of social interactions, as well as recommendation for pedagogical innovations. The last section establishes a definition of creativity and the conditions under which creativity is likely to emerge, where I show the role of standard versus network analysis for the study of this social phenomena. Taking all these elements together, I expect this section will allow a comprehensive understanding for the ways in which researchers might approximate to the study of creativity in education, and some alternatives to introduce opportunities for creativity in the classroom, in connection with mechanisms for social interaction as necessary to explore the complexity of social learning and the generation of good ideas.

2.1 Problem Solving in Physics Education

Problem solving is arguably one of most studied topics in the physics education literature, as it involves complex cognitive processes connected with physics content that provide a fertile field to investigate the different conditions and/or strategies that enable good performance on physics problems. I designed this sub-section to outline first the problem categories identified in the literature and their purposes. Second, I describe the learning effects of problem solving on the dichotomies novice-experts problem solvers, and individual-collective tasks. This is followed by a presentation of best practices for designing and administering problems, including a description of the problem solving strategies designed to guide students to adopt expert-like problem solving behaviors. Finally, I describe the research methods utilized in this study of problem solving in physics education.

2.1.1 Problem Categories

To understand the arguments and ideas presented here, first it is important to have a clear definition of what a problem is. Jonassen (2000) provides a general definition for problems using two critical attributes: “1. Problems are unknown entities in some particular contextual scenario; and 2. Finding the unknown must have a social, cultural, and intellectual value” (p. 65). These attributes impose interesting conditions for labeling learning activities as problems, because the ultimate responsibility of categorizing that task upfront as a problem rests on the individual who will attempt to solve it, given that he/she must perceive that the activity is indeed unknown, and engaging in it might bring intellectual value. Even though physics educators tend to consider most learning activities as problems, under Joanassen's attributes, the expertise and previous experience would play a key on whether a student perceives the task as a problem or simple exercise. In the case of experts, these should be perceived as exercises, or activities with certain degree of familiarity and little ignored elements rather than problems. Moreover, solving problems consists of finding what is unknown as a product of systematic cognitive operations, which requires an initial mental representation of the problem based on the available knowledge related to the situation. The second step demands that solvers use their representations and appropriate resources aiming for a dialogue between their thinking process and the problem in front (Jonassen, 2000).

From a brief analysis of the research literature in Physics Education Research (PER) on problem solving, it is possible to identify two major types of problems used to understand students' learning processes: (1) close-ended, well-structured or well-defined; and (2) open-ended, ill-structured or ill-defined, or what Heller and Hollabaugh (1992) called in context-rich problems. Although context-rich problems are originally defined to be open-ended, these are often designed and constrained to be consistent with the learning goals embedded in a classrooms (i.e., learning physics), and thus end up being relatively less open-ended than other examples of ill-structured problems. Further, within well-defined problems, one may also identify a minor sub-division of qualitative and quantitative problems. Every research article considered for writing this paper utilized at least one of the mentioned problem categories either to differentiate subjects between experts and novices problem solvers, or to understand individual or collective processes for solving problem and decision-making.

According to Jonassen (1997; cited by Shin et al. (2003)), well-defined problems are situations that present all possible elements that allow finding a known and unique solution. Consistently, these problems describe a particular scenario that demands the use of a limited number of rules and principles (e.g. algebra and physics principles). These procedures tend to be well organized, constrained to certain parameters (e.g., initial and/or the final conditions on a motion problem in kinematics), and with predictable actions that are frequently used to solve similar problems. In PER, these problems mirror simplified and idealized situations that have little to no connection with students' real world experience (Heller and Hollabaugh, 1992). Based on this description, one could almost immediately think of algebra or calculus-based physics problems, or the traditional situations presented on physics textbooks (Chi et al., 1981; Larkin et al., 1980), which required mathematical representations and algebraic procedures. Math-based problems tend to present simplify versions of reality, appropriate for the implementation of mathematical representations of physics concepts and principles. Here, educators have assumed the existence of a strong relationship between implementing mathematical representations of physics content and mastering these conceptual principles (Dufresne et al., 1992; Kohl and Finkelstein, 2008). Nonetheless, research evidence has found disturbing results on this matter. Studies conducted by Kim and Pak (2002), and Byun and Lee (2014) found that even after solving over a thousand physics problems, students did not show the expected conceptual understanding of physics principles and laws. These results reveal the dangers of mechanizing problems and engaging in superficial use of formulae for finding solutions.

Byun and Lee (2014) suggest that probably the best predictor of academic success in testing and physics understanding lies on the strategies used for solving the problems. This suggestion is consistent with other studies that have attempted to differentiate problem-solving processes between experts and novices (Chi et al., 1981;

Larkin et al., 1980; Leonard et al., 1996; Kohl and Finkelstein, 2008; Sabella and Redish, 2007). Byun and Lee (2014), differentiate between Knowledge-Development, and Means-End and Random strategies for solving problems, being the former the one that leads to better conceptual outcomes. In simple words, Knowledge-Development refers to beginning by building an extensive conceptual understanding before attempting to solve problems, or engaging in the use of mathematical representations. Conversely, Means-End consists of focusing on the problem goals' and then conceptual meanings, whereas through Random, students navigate the problem and their conceptual development simultaneously without a particular order. In coherence with the evidence by Byun and Lee (2014), well-structured mathematical problems tend to push students to utilize Means-End strategy, or 'plug-and-chug', known as the practice of finding the formulae that best fit the problem, and plugging the pertinent numerical values to find solutions, a behavior typically associated with novices (Dufresne et al., 1992). Larkin et al. (1980), explained the lack of learning opportunities associated with close-ended problems, as student working backwards, from the goal of the problem (i.e., finding a numerical value), and overlooking the conceptual physics associated with solving it (Heller and Hollabaugh, 1992).

Because well-defined math-based problems have shown to push students away from conceptual development, physics educators have also designed and used qualitative problems to highlight students' learning and conceptual development (Buteler and Coleoni, 2016; Harlow et al., 2016; Meltzer, 2005; Shing, 2008). Qualitative problems consist of physical situations where students are required to describe the nature of the phenomenon using only conceptual physics. Unlike traditional math-based problems, qualitative problems rely only on students' phenomenological understanding, rather than algebra or calculus procedures. Moreover, Singh (2008) introduced an interesting methodological application based on traditional quantitative and qualitative problems, by designing pairs of isomorphic problems. These pairs of isomorphic problems consist of learning activities that address the same underlying physics principles, yet are presented to highlight different physics representations. Similarly, Meltzer (2005) labelled pairs of isomorphic problems depending on whether these introduced verbal or diagrammatic representations.

At the opposite end of the spectrum from well-defined problems, are ill-defined, ill-structured, open-ended situations or real world problems (Fortus, 2008). Ill-structured problems lack constraining conditions or information that would guide individuals to find unique solutions, introducing high levels of uncertainty associated with a spectrum of possible solutions, rules or strategies on how to proceed to generate them (Shin et al., 2003). In PER, Heller and Hollabaugh (1992) proposed the design of context-rich problems as an alternative to traditional textbook physics activities. These problems meet the characteristics of ill-defined problems to the extent that do not limit subjects to unique and already known solutions. Normally, context-rich problems are introduced in the form of highly detailed contextual situations, with either missing or added information. For obvious reasons, the context under which these problems are introduced (i.e., a physics classroom), immediately added constrains not necessarily to the problem itself, but to the possible outcomes, as subjects would develop a general sense of the academic expectations for their solutions. However, and regardless of whether students are conscious of the outcome's expectations, these problems would demand some degree of decision-making, associated with the ability to generate assumptions on physics issues, in such a way that would transform the ill-structured problem into a well-structured one (Fortus, 2008).

In terms of a problem's cognitive load, Teodorescu et al. (2013) generated a taxonomy of introductory physics problems, where they described the cognitive demand required to solve learning activities on four levels: 1. Retrieval of information (recalling and executing); 2. Comprehension (integrating and symbolizing); 3. Analysis (matching, classifying, analyzing errors, generalizing and specifying); and 4. Knowledge utilization (decision making, overcoming obstacles, experimenting and investigating). Accordingly, and based on the features of well-structured problems, whether quantitative or qualitative, the highest cognitive level typically reached is "analysis." The exception is that some problems may, by design, include obstacles that solvers need to overcome, and therefore would require knowledge utilization, the highest level of cognitive demand. In contrast, ill-structured problems are designed to demand decision making from the beginning. For instance, the problem of generating a physics activity is ill-structured in the sense that forces students to make decisions over multiple domains, such as the age level of the individuals who will face it, content, questions, and other conditions that are necessary to give the activity an appropriate structure, even though this may end up being ill-structured.

2.1.2 Research Purpose of Assigning Different Problems

In PER, physics problems have been used for two important purposes: encouraging knowledge building and expert-like behavior (Hardy et al., 2014; Leinonen et al., 2017; Shing, 2008); and revealing how subjects process information, understand content and strategize how to solve problems individually and in groups (Benckert and Petterson, 2008; Kohl and Finkelstein, 2008; Sabella and Redish, 2007). It is fair to mention that problem design and implementation should always try to meet the first goal of encouraging physics learning. In addition, the PER literature had proposed three major dimensions under which one would identify the implementation of physics problems for the mentioned objective: First, to understand the dichotomy between experts and novices problems solvers; second, as a mechanism to understand students' conceptual development and how learning is built; and third, to reveal the type of strategies subjects use when solving problems, or to test the effectiveness of defined guidelines to address these problems. A deeper understanding of each of these research goals would lead us to perceive them as highly connected rather than separated. For instance, one might think that the second and third dimension emerged from the study of experts versus novices, to the extent that both types of students would display different levels of conceptual development, based on a more or less interconnected conceptual network (Dufresne et al., 1992; Jonassen, 2000). Consequently, the degree of conceptual interconnectivity may guide them to use novice or expert-like strategies when solving problems (Byun and Lee, 2014).

From the lens of experts versus novices, Larkin et al. (1980) reviewed empirical evidence on well-structured problem-solving performance from different subjects, in order to explore whether there were differences between novices and experts. Later, Chi et al. (1981) used well-defined math-based problems to explore experts and novices problem categorization based on their problem representations. In this context, problem representations are defined as the network of conceptual meanings, or cognitive structure associated with the problem, and developed on the basis of related content knowledge, in this case, conceptual Newtonian physics. Similarly, Meltzer (2005) attempted to measure expertise among undergraduate students by exploring the proportion of correct responses on verbal and diagrammatic representation of a very similar well-structured problem. Meltzer tested students' ability to recognize underlying physics principles and various representations. A different study conducted by Kohl and Finkelstein (2008) explored the pattern of multiple representations that novices and experts use when facing and solving well-structured math-based problems. Differently from the studies above where subjects were encouraged to activate their knowledge based on how problems are designed and represented, Kohl and Finkelstein referred to subjects' generated representations like diagrams, graphs and equations, as strategic processes for solving problems. Among other studies that have tried to discover how subjects solve problems in physics education, Sabella and Redish (2007) attempted to test a model of knowledge organization by studying subjects' ability to solve well-structured math-based problems. Finally, Sherin (2006) used conceptual and math-based well-structured problems to explore the role intuitive knowledge in the use of equations in problem solving, and their transition towards expertise.

Later, Shing (2008) moved towards encouraging conceptual development and expertise through the use of pairs of quantitative and qualitative isomorphic well-structured physics problems. Singh argued that having two similar problems would guide students into identifying the underlying similarities and physics principles, thus, encouraging higher order representations rather than superficial models and categorizations. Compared to the previous studies, Singh used problems not only to describe students representations, but as an instruction mechanism that would potentially guide students to develop expert-like ability. Similarly, Heller et al. (1992) designed context-rich problems as group and individual activities, instructing their students to solve them by following a five-step problem solving strategy: 1. Visualize the problem; 2. Describe the problem in physics terms; 3. Plan a solution; 4. Execute the plan; 5. Check and evaluate. In the same line, but using well-structured math-based problems, Leonard et al. (1996) performed a similar study using qualitative writing strategy to highlight the conceptual physics associated with the problems. A similar set of authors, Dufresne et al. (1992) designed computer-based environments where novice problem solvers were constrained to engage in a skilled problem-solver behavior, that is, simulate experts problem solving strategies. Given that problem-solving strategies in itself tend to be insufficient for transitioning novices to expert cognitive development, authors assume that 'forcing' behaviors to imitate experts might constitute a useful technique for promoting problem-solving abilities.

So far, with the exception of Heller et al. (1992), all problems have consisted of individual well-structured activities. However, Heller et al. (1992) found interesting evidence that groups performed better than individuals in solving context-rich problems. Others, like Benckert and Petterson (2008) used similar context-rich problems on relativity, wave motion and rotational dynamics as group activities, and explored the learning and problem-solving process of three groups. Moreover, conceptual problems have been frequently used as group activities, because, as oppose to math-based, these provide a better ground for conceptual discussion and argumentation, making it easier to study the different understandings and strategies individuals and groups engaged. Related evidence can be found in Buteler and Coleoni (2016), Harlow et al. (2016), or in Leinonen et al. (2017).

Besides context-rich problems, there has not been many uses for ill-structured problems in PER, thus providing a sense of how embedded well-structured physics problems are in the field. One may be tempted to think that the constant use of well-structured problems, either qualitative or math-based, along with training on the right strategies, as appropriate learning activities for subjects to be capable of developing the expected conceptual understandings and expertise for real world situations. However, Shin et al. (2003) used well and ill-structured problems in astronomy in familiar and unfamiliar contexts to test whether these types of problems were predicted by the similar personal attributes. Unsurprisingly, while well-structured problems are predicted by subjects' justification skills and domain knowledge, ill-structured problems demanded additional abilities, like structural knowledge, science attitudes and cognitive regulation. Later, Fortus (2008) studied the importance of making assumptions when solving ill-structured mechanics problems on experts and novices. Results indicated that even experts struggled to make the adequate assumptions (i.e., on the physics variables and principles involved, and on the absolute or relative magnitudes of the variables) for constraining ill-structured problems into their unique solutions.

2.1.3 Benefits of Problem Solving and its Effects on Different Populations

In this section, I addressed the effects of different types of problems on experts and novices, and as individual and group activities. The former dichotomy has taken most of the attention in PER, motivating the emergence of several methodological interventions to encourage expertise in physics problem solving. Moreover, solving problems as group activities has demonstrated to provide richer learning outcomes compared to individual performance on complex context-rich problem (Heller and Hollabaugh, 1992).

Experts versus Novices

.According to research evidence, experts and novices manifest a different cognitive architecture, or network of domain-specific resources. Experts show a rich, interconnected body of concepts and relations that facilitates problem categorization (Chi et al., 1981), identification of the essential concepts and principles required by problems, and utilize a set of practical procedures that are grounded on the importance of understanding these concepts. Sherin (2006) used p-prime terminology (diSessa, 1993), or intuitively developed physics ideas, to explain the differences between these groups. In the mind of a novice, p-primes or intuitive pre-instructional schemas live in a flat weightless conceptual networks, and it is not after having a meaningful learning experiences that a novice's cognitive structure would change and evolve, generating a hierarchical and denser network of representations (expert). This new network of resources present now a diversity of weights depending on the importance and use of the available resources, or schemata (Dufresne et al., 1992; Sabella and Redish, 2007). Consequently, experts would experience little to no cognitive challenge in the presence of traditional physics problems, and are likely to perform better, faster through the implementation of consistent strategies (Kohl and Finkelstein, 2008).

An interesting method for understanding the effects different types of physics problems might have on experts and novices was proposed by Chi et al. (1981), when they asked participants to first categorize traditional physics problems, and then talk about the physics information that these categories would trigger. The fact that certain situations, in this case problems, would immediately activate students' ideas in the matter becomes useful to categorize subjects based on what they know, and anticipate possible responses. Consistent with the cognitive description of experts and novices, research evidence has found that novices categorize problems by paying attention to superficial features presented in forms of diagrams or in the problem description (**?**Shing, 2008). Associating surface problem characteristics with mathematical and physical representations leads to memorization techniques that would guide to ineffective problem-solving performance. The recalling difference between novices and experts refers to associating problem features with set of equations instead of principles, known as bottom-up logic (Dufresne et al., 1992; Larkin et al., 1980). In the face of a new problem, the use of bottom-up logic would make novices spend time and energy finding the right equation rather than the right principle. In contrast, experts are oriented to use top-down logic, that is, they start from general principles, heading down to the mathematical representations needed to solve problems.

Traditional physics education practices rely strongly on textbook problems, math-based and well-defined, consistent with the most frequent type of problem mentioned and use in the PER literature. The effects of these traditional problems were studied by Kim and Pak (2002), and by Byun and Lee (2014), whose results are discouraging to say the least, particularly for novices. Accordingly, textbook problems are proven highly ineffective for knowledge building and conceptual development, no matter how may problems students solve. Mechanization and reproduction of mathematical algorithms to find unique solutions encourages bottoms-up logic, thus, pushing students away from the needed physics understanding. Byun and Lee (2014) pointed out that the main difference lies not in the number of problems, but rather in the strategies used to solve them. While experts enact knowledge driven strategies by paying attention to conceptual ideas before attempting mathematical procedures (i.e., Knowledge-Development), (Larkin et al., 1980; Sweller, 1988), novices aim for equations without clear directions, and motivated by finding the right solution (i.e., Means-End and Random). Therefore, traditional math-based problems by themselves are far from helping novices to develop complex and coherent resource networks.

Furthermore, achieving expertise through well-structured problems does not necessarily translate into successful performances with real world or ill-structured problems. There are different abilities and skills needed to define and generate solutions in the latter activities that are not required in the former case. For instance,Shin et al. (2003) found evidence that good performance in well and ill-structured problems is predicted by different set of attributes. In detail, for successfully solving well-defined problems, subjects need well-structured domain knowledge and justification skills, which is consistent with cognitive evidence on expert solving traditional math-based problems. Similarly, performance on ill-structured problems is associated with having justification skills, well-structured domain knowledge, and science attitudes, but only when these problems are designed from familiar contexts. Yet, when ill-structured problems are contextualized in unfamiliar scenarios, justification skills, well-structured domain knowledge and additional metacognitive set of skills associated with regulation of cognition (i.e., information selection) are proven to be a significant predictors. Not surprisingly, problems in general demand well-organized and integrated knowledge for generating or finding solutions. Yet, while well-structured problems tend to be rather familiar for students, and they can support their process by recalling past experiences, ill-structured and unfamiliar problems depend strongly on case reasoning or familiarity (Fortus, 2008). The lack of experience in facing ill-structured problems is consider a key reason for why students may find these problems more difficult. Similarly, Fortus (2008) found interesting differences in the ways novices and experts physicists faced and solved well and ill-defined problems. According to Rietman (1964), the fundamental ability to solve ill-defined problems consists of making appropriate constraining assumptions that would transform the problem into a well-structured one, which based on Fortus's results, is the most difficult step for all participants. In addition, evidence also suggests that prior experience in making assumptions for solving ill-structured problems is what separates subjects from completing the task Fortus (2008). Therefore, with this information, it is fair to state that exposure to ill-structured problems would facilitate solving real-world problems, by helping the subject gain experience and possibly activating the metacognitive skills found significant in Shin et al. (2003). This statement is consistent with what Jonassen (2000) considers a feature to classify problem. Familiarity with certain types of problems is perceived as having developed the schemas that enable subjects address problems (Sweller, 1988), whereas lack of experience might reflect the absence of appropriate schemas (i.e., conceptual network), nor strategies to find suitable solutions. Consequently, domain and structural knowledge would translate into a cognitive structure that supports the understanding and classification of problems, in such a way that would facilitates information recall and operationalization of problem solving strategies. Given that familiarity and prior experience could make a difference on ill-structured problems, pushing students to create their own physics problems might be an alternative to this issue. The experience of Hardy et al. (2014), which consisted of students creating multiple-choice questions, produced positive learning outcomes, especially for low and middle performance students. The uniqueness of these activities lays on the lack of constraining conditions, normally present on context-rich or other real world problems, which would not restrict students' performance in the case that prior experience and problem description do not match. Yet, even in this case subjects may struggle due to their reduced experience creating (i.e., making assumptions) (Fortus, 2008).

Collaboration versus Individual Problem Solving

Finally, problems as group activities have shown positive effects compared to individual performance. Research evidence from Heller and Hollabaugh (1992), and Heller et al. (1992), using context-rich (ill-defined) problems in mechanics demonstrated the groups provided better problem solutions that individuals working alone. These results suggest a positive effect of collaboration and context-rich problems together. The mentioned limitations for addressing ill-structured problems as individual tasks might be overcome through collaboration, as it might provide a platform for individuals with diverse prior experiences and cognitive strategies to work together. Besides the positive outcomes found by Heller and colleagues, other studies mentioned here have not provided differences between individual and group work. Nevertheless, some authors have assumed the advantage of this practice, and conducted studies to understand group collaboration, its general effects on academic performance (Harlow et al., 2016), and the nature of students' conceptual discussions to solve conceptual and math-based problems (Benckert and Petterson, 2008; Buteler and Coleoni, 2016; Leinonen et al., 2017). Further, implementation of qualitative problems (e.g., some tutorials activities) as individual or group activities has encouraged students to focus on conceptual principles and physical laws, encouraging top-down logic associated with a hierarchical resource network. Singh's (2008) study with isomorphic problem representations provides important evidence on this matter. Even though the use of pairs of quantitative and qualitative problems did not improve significantly students' performance on math-based problems, there were some significant positive changes on conceptual responses. This evidence suggest that having both quantitative and qualitative problem representations would help subjects to more clearly identify concepts and principles associated with the problem. Accordingly, it would be fair to declare that conceptual problems might shift students' orientations to solve problems, from math to knowledge driven.

2.1.4 Best Practices for Problem Design and Problem Solving Strategies

Based on the research-based evidence presented in the previous section, one may have a general sense of what types of problems are more appropriate for physics learning and conceptual development. This evidence guides us to perceive all types of problems as necessary for appropriate and integral physics learnings, with the awareness that, product of their nature and cognitive demand (Teodorescu et al., 2013), these problems are designed to meet different purposes. It has been established that traditional well-structured and math-based problems facilitate students' use of mathematical representations and algebraic performance for problem solving. Even though this skill set does not reflect conceptual understanding in physics (Byun and Lee, 2014; Kim and Pak, 2002), it might be perceived as a baseline standard in the use and manipulation (i.e., algebra and calculus) of physics concepts in their mathematical representations. This argument is supported by Singh's (2008) findings, where students are able to improve their performance in conceptual problems when these were paired with its quantitative version, indicating that a familiar math-based representation could boost cognitive associations with conceptual physics. This led us to assume that both types of learning activities (i.e., conceptual and math-based) are required for effective physics instruction, as qualitative problems would shift students attention, particularly for novices, from equation driven strategies (i.e., means-end) to knowledge development ones. Learning methodologies based on a combination of both types of well-structured problems are present in tutorial activities (Harlow et al., 2016; Leinonen et al., 2017). A useful recommendation for problems' design, either quantitative or qualitative, refers to the use of detailed context descriptions, in such a way that the activities would reflect real world phenomenon and target personal experiences. These designs not need to mirror context-rich features in the sense that they are open-ended, but include variables to mirror students' reality. Real context problems may contribute to subjects' overall familiarity, or schemas for effective problem-solving and transfer, as suggested by Jonassen (2000).

Moreover, given that proficiency on well-structured problems does not reflect one's ability to solve ill-structured or real world problems Shin et al. (2003), it is necessary to design and implement these activities for students to engage in the creative and metacognitive processes these entail. Physics and problem solving skills should not be boxed within the limits of domain-specific activities and their idealized problems. This calls for attention and consideration of learning activities that would encourage problem solving skills that can be transferred to different scenarios and contexts. The problem innovation made by Heller and Hollabaugh (1992) is encouraging in that matter, as it removes simplifications and clean data by providing contexts that many could relate, so that students could perceive how physics content is implemented in multiple ways in the real world, as well as opportunities to engage in assumption making (Fortus, 2008). Further, and even though context-rich problems are defined as open-ended, one may say that the social context (i.e., physics classrooms) where these are use, restricts the ways these are perceived, and the spectrum of possible outcomes. That is, no matter how open-ended the situation is, the context of the class would immediately provide a baseline standard for what it is expected (i.e., appropriate use of physics concepts, principles and/or laws), which is rather obvious, given that these outcomes most likely will be subject to evaluation. Differently, Hardy et al. (2014) presents a type of problem with lower constraints than context-rich problems, which consists of students generating questions. This learning activity relies heavily on students' intentions, expectations and abilities to generate assumptions (i.e., creativity), and has shown to be an appropriate way to assess learning and conceptual development (Mestre, 2002).

Taking all these problems together, it would be rather simple to suggest that all different types of problems are necessary for training in physics and problem solving. Students need to develop the abilities associated with manipulating mathematical representations of physics concepts and principles in order to solve problems, well provided by traditional textbook problem (e.g., Chi et al, 1981; Larkin et al., 1980; Kohl and Finkelstein, 2008), along with an appropriate conceptual understanding, highlighted by qualitative problems (e.g., Buteler and Coleoni, 2016). Yet, both mathematical and conceptual abilities for well-structured problems are not enough for solving ill-structured physics problems in unfamiliar situations. An integral skill set for problem solving in physics and for real world situations associated with this domain, demands a well-structured conceptual network able to manage multiple representations (Khol and Finkelstein, 2008), along with regulation of cognition and justification skills (Shing, et al., 2003), as well as the ability to generate useful assumptions to creatively constrain these situations (Fortus, 2008).

The different processes experts and novices engaged in when solving problems has motivated serious efforts for creating strategies that would emulate experts' performance, and would guide less capable students (Docktor et al., 2015; Dufresne et al., 1992; Gaigher et al., 2007; Heller et al., 1992). These efforts are grounded on the assumption that problems, regardless of their nature and structure, are not enough for helping novices evolve towards expertise, thus needing external guidelines and instructions to achieve positive results. The strategy proposed by Heller and colleagues (1992) describes five-steps that orient students to conduct different abstract and mathematical transformations of the problem into different representations (1. Visualize the problem; 2. Describe the problem in physics terms; 3. Plan a solution; 4. Execute the plan; and 5. Check and evaluate). Positive academic results support the use and implementation of this strategy for addressing problems. Later, Leonard et al. (1996) focused on the qualitative dimension of solving problems and proposed a three-step strategy, that they later called Conceptual Problem Solving (CPS) (Docktor et al., 2015). The first step consists of finding principles or concepts that might be appropriate for the problem. Then, a justification step requires participants to explain the reasons for selecting those concepts and principles. Finally, students are instructed to describe the procedures through which they will arrive to a solution. These problem-solving 'rules' are relatively easy to implement in physics classrooms, as they do not demand major innovations at curriculum level, and can be used with different types of problems. However, these would require consistent practice and use if one were to expect and evidence a transition towards expert-like behaviors.

2.1.5 Collaboration and Group Performance

In the absence of formal instruction on these problem-solving strategies, educators can rely on student collaboration as an informal, yet not necessarily less effective, way of accessing appropriate conceptual ideas, along with tactics and procedures to solve problems. Vygotzky's zone of proximal development (ZPD) (1978) provides strong support for collaboration, particularly when students learn by interacting with more capable others. Yet, there is uncertainty on whether the others in the group are indeed more capable. Even if that were the case, would they share and collaborate in such a way that every team member would benefit from it? The issues associated with effective collaboration in physics classroom were addressed by Heller and Hollabaugh (1992), and in less detail by Harlow et al (2016). Heller and Hollabaugh considered certain group characteristics that would guide groups to success, like size, heterogeneity and member's personality. According to their results, group-size does matter, being groups of three and four the ones that generated the better problem outcomes. Results also supported by Leinonen, et al (2017). In terms of group composition, heterogeneous groups tend to perform better, with medium and low ability students complying an important role in regulating groups' processes, and suggesting simple but effective ideas. Moreover, even in appropriate sized and mixed-ability groups, performance can be affected by dominant personalities and conflict avoidance. To overcome these issues, authors attempt to assigned roles to each member, yet the initial plan of rotating roles relies too much on students being able to dissociate themselves from the responsibilities each role entails, from one session to the next. Further, Johnson et al. (1986) proposed two conditions that would facilitate students' collaboration for problem solving: positive interdependence, or students' belief that success is a collective rather than individual effort; and individual accountability, or the fact that each students assumes responsibility for mastering the studied material. With this information, one may start thinking about clear conditions and requirements for effective collaboration in physics problem solving. For example, students would need to be trained on how to follow and meet the latter conditions for positive collaboration. Moreover, a good combination of different types of problems as individual activities might be needed to set a cognitive and conceptual ground for students to collaborate, as they need a basic physics understanding prior to engagement in group problem solving (Benckert and Pettersson, 2008), and especially if the problem is ill-structured.

2.1.6 Research Methods in Physics Problem Solving

The studies described here allowed me to differentiate two big categories under which research on physics problem solving has been conducted. First, most research has focused on describing or exploring the problem solving processes individual or groups engaged in when facing physics problems of diverse nature, or its association with conceptual development and academic success. Some researchers have used theories for conceptual development like Coordination Class Theory (Buteler and Coleini, 2016), or cognitive models like the convergent thinking model, proposed by Sabella and Redish (2007), to understand the different ways learners develop meanings and problem representations. Other authors have paid attention to the conditions under which students are more effective in solving problems (e.g., Benckert and Petterson, 2008; Heller, Keith and Anderson, 1992; Leinonen et al., 2017), for instance, providing guidelines for group formation and performance. Second, PER has also focused on testing methodological interventions to improve students' ability to solve problems and build appropriate physics meanings. Most of these interventions are grounded on the use of problem solving strategies, like qualitative problem solving (Leonard et al. 1996), or Conceptual Problem Solving strategy (Docktor et al., 2015), while others implemented learning activities, like generating multiple choice questions (Hardy et al., 2014), or isomorphic physics problems for knowledge building.

There is a fair amount of variation in the designs used to study problem solving in physics. The majority of these can be considered case studies, where research subjects, with diverse degrees of physics expertise are assigned to solve problems, either individually or in groups. For instance, Chi et al. (1981) designed three experiments to explore first, how experts (eight PhDs) and novices (eight undergraduates) categorize traditional physics problems. Then, with the help of a different pair of experts and novices, and using the label categories generated by the subjects, they explored the physics knowledge these categories would activate in both populations. Here, data consisted of students' problem categorizations and oral responses, which were recorded for analysis of time. Problem categorization was measured by sorting problems based on what subjects consider similar attributes. Their performance on this task was also studied using how quick they were able to categorize problems. Later, using the label categories, authors explored knowledge activation in experts and novices using representations of conceptual networks.

Similar research designs, but with video data collection, were found in Fortus's (2008) study of experts and novices solving well and ill-defined physics problems, which used the IDEAL problem solving model developed by Bransford and Stein (1984) (1. Identify the problem, 2. Define and represent the problem, 3. Explore possible strategies, 4. Act on the strategies, and 5. Look back and evaluate the effects of your activities.), as a baseline framework for analyzing subjects' performance in solving problems. Additionally, Kohl and Finkelstein's (2008) work on students' use of multiple representations is based on several case studies conducted with a small sample of experts (5 graduate students) and novices (11 undergraduates), who were asked to solve electrostatics and mechanics problems during clinical interviews. First, authors focused on representation use as a function of time, and then, coded for the types of activities subjects engaged in during the problem solving. With both levels of analysis, Kohl and Finkelstein were able to map how students utilize different representations and activities to address physics problems. Furthermore, Sabella and Redish (2007), and Sherin (2006), replicate some features of Kohl and Finkelstein's study, in the sense that both decided to use similar physics problems to be solved by college physics students, and record their performance on an interview, or through video. Sabella and Redish used the information provided through thinking aloud protocols to demonstrate how knowledge is built and connected in the cognitive network, and the extent to which it is locally and/or globally coherent. Local coherence refers, for instance, when someone deeply understands the differences in nature and uses of concepts associated with force, and associates common use to them. Then, if these sets of force concepts are use together with concepts related to work and energy concepts, but identified as different, then knowledge is globally coherent. In Sherin (2006), the analytical process is similar, yet instead of focusing on a detailed thinking model, the author paid attention to diSessas's (1993) p-primes or phenomenological primitives, represented by intuitive or pre-instructional knowledge. The theory suggests that through cognitive development and learning, p-primes would develop hierarchical networks that would ease information recall and facilitate problem solving.

Other studies have focused on groups solving problems, whether to explore their processes and quality of members' ideas (Benckert and Petterson, 2008; Buteler and Coleoni, 2016; Leinonen, et al., 2017), or to study the effects of group composition on performance (Harlow, et al., 2017; Heller and Hollabaugh, 1992). In more detail, Benckert and Petterson (2008), paid attention to three groups formed by three and four college students, while they solved context-rich problems on general relativity, sound and rotational mechanics. Video recording of groups allow researchers to identify the fundamental strategies that guided performance towards appropriate understandings and solutions. Later, Buteler and Coleoni (2016), interviewed three undergraduate students while solving a conceptual problem in hydrostatic, with the goal of understand students thinking processes from the lens of Coordination Class Theory (CCT). In general terms, CCT is defined upon two important mechanisms: read-out strategies that allow individuals to pay attention to particular pieces of information; and an inferential net consisting of all the possible inferences people can make via incorporation, displacement, articulation, alignment and span of information highlighted from read-out strategies.

Moreover, Leinonen et al. (2017) explored peer discussion on an undergraduate introductory physics class based on physics tutorials. Along with the goal of understanding how students interact and discuss physics topics, authors wanted to test the degree to which type of discussion would predict success. Data was collected on pre and post tutorials worksheets, and audio recordings of groups working on the tutorial activities (qualitative and quantitative problems). Students' worksheets were used to explore their explanations, which were later labeled as acceptable, inadequate, and empty or uncategorized, whereas group discussion was analyzed by means of data-driven content analysis. Furthermore, Heller and Hollabaugh (1992) performed their quasi-experiment using different individual and different group compositions to test their effectiveness in solving context-rich problems through a problem-solving strategy. They utilized students and groups' written problem responses, along with observations of groups' interactions to describe which group characteristics (e.g., size, gender composition, personality characteristics, assigning and rotating roles) guided better performance. Differently, Harlow et al. (2017) attempted to test group effectiveness by measuring FCI (Force Concept Inventory) score gains on an introductory class. This research methodology differed from other studies in that it relied completely on students' survey response, and it did not include qualitative data collection.

Following with more quantitative methodologies, Kim and Pak (2002), and Byun and Lee (2014) performed different designs to determine whether there was an association between the number of textbook physics problems students solved, and their conceptual understanding. Kim and Pak administered two math and mechanics test

(Halloun and Hestenes, 1985; Hestenes and Wells, 1992) to determine initial level of preparation, and a questionnaire designed to explore the amount of problems answered by subjects. Later, authors used a set of tutorial activities to study possible conceptual difficulties. In the case of Byun and Lee (2014), the study is conducted with 49 students who were divided into four groups depending on the number of problems solved, reported on a survey. Additional data consisted of FCI scores, and mid-term examination scores. Differently from Kim and Pak (2002), researchers interviewed one member of each group three times, aiming for qualitative information on their problem-solving processes.

Some research involved testing the effects of problem solving techniques, or instruments designed to help students move in the direction of experts. For instance, problem-solving techniques, like computed-based Hierarchical Analysis Tool (HAT) or Equation Sorting Tool (ETS) introduced by Dufresne et al. (1992) were administered over a period of three weeks and eight experimental sessions with physics undergraduate students. HAT environment allows participants to select the underlying physics principle associated with the problem, moving from general, to principles that are more specific. However, ETS environment will reflect a novice approach for solving problems, allowing subjects to cue from surface features to pull equations and tackle problems. For testing HAT and ETS's effect over a possible students' shift towards deeper physics understandings, Dufresne and colleagues assigned one problem-solving tool to two different groups, leaving a control group for comparison.

Longer-term interventions involved the acquisition and development of problem solving strategies and skills, or simple adjustment to a consistent practice, like students generating questions. In the latter case, Hardy et al. (2014) asked students to generate their own multiple-choice questions using PeerWise online portal, which allowed them to submit, answer and review questions posted by others. The study follows a quasi-experimental design with one group, with data consisting of students' participation provided by PeerWise, and students' ability measured prior to the introduction of the portal to the course. From the lens of methodological interventions to support appropriate problem solving skills, Leonard et al. (1996) implemented qualitative writing strategies in a calculus-based undergraduate physics class. The study did not require a major methodological innovation nor implementation, yet the strategy was used every time a problem was introduced in the class. Here, the instructor dedicated time to present the qualitative strategy, and differentiate it from the solution. Data was collected on three class activities: 1. Strategy writing task; 2. Problem categorization task; and 3. Recall task administered months after the intervention. Finally, Gaigher et al. (2007), implemented another quasi-experimental design, with experimental and control groups, and pre and post-test. This research used 30-min traditional in-class activities to test a 7-step problem-solving strategy designed to facilitate qualitative problem interpretation. Students' tests solutions, scripts and video recordings were used as data, and analyzed from the lens of extended semantic model developed by Greeno (1989). Greeno's model includes four domains of knowledge: 1. Concrete (physical objects and domains); 2. Model (models of reality and abstractions); 3. Abstract (concepts, laws and principles); and 4. Symbolic (language and algebra). Consequently, the framework allows the creation of networks connecting students' representations on each of these four domains.

In sum, one could say that PER on problem solving has taken a variety of shapes, adopting qualitative, quantitative and mix-methods perspectives to provide research-based evidence. I would argue that there are common methods and forms of data collection associated with similar research questions. Exploratory and more descriptive studies show a higher tendency to rely on deep observations and interviews, particularly if the research goals refer to how individuals or groups face and solve problems.

Differently, methodological interventions associated with innovative approaches to solve problems, or even the implementation of new testing instruments rest on designs similar to quasi-experiments (real experiments are unrealistic in social science), with one or more groups, and data associated to students written work, performance or engagement. Finally, due to the content oriented nature of PER studies on problem solving, it is inevitable that physics content will be the primary lens for examining students' performance, thus making every other measurements, strategy or theoretical model for data analysis, an auxiliary lens to complement, and somehow give sense to the physics-related evidence.

2.2 Social Networks in Education

The motivation for conducting this study has come from the literature of social network, which provide an methodological and analytical lens for the research of social processes, like learning and problem solving. This section begins with a description of networks, their elements and basic principles. Later, I describe the benefits for using Social Network Analysis (SNA) as a methodological tool relative to standard methodologies, and its limitations. Finally, I present the key features to conceptualize school classrooms as social networks, and the nature of relevant networks in the literature of SNA in education.

2.2.1 What is Social Network Analysis?

Social Network Analysis (SNA) consists of a set of theoretical and methodological approaches used to understand social systems, the emergence of social structures, and the possible consequences of social relationships or links between different set of actors or nodes within a given context. Grunspan et al. (2014), suggest that SNA attempts to provide research-based evidence on two comprehensive and related domains: 1) The extent to which contextual variables encourage social relationships and 2) the influence of social networks on group outcomes. To expand on these two domains, the first set of research questions tries to understand to extent to which contextual variables or personal attributes encourage the formation of social relationships. For instance, Brewe et al. considered contextual features introduced through Modelling Instruction (MI), a methodological innovation for learning physics, and explored formation of learning communities as a measure of participation and engagement. Further, McFarland et al. (2014) took a more inclusive approach, as they addressed contextual and perceived attributes to explore the nature of tie formation using a theory of network ecology. Turning to the second domain, other efforts have tried to provide evidence on the consequences or influences of different social structures over individual or group-level outcomes (Bruun and Brewer, 2013; Smith and Peterson, 2016). A study conducted by Bruun and Brewer (2013) presents evidence that in-class social communication, along with others centrality measurements (defined later), predict future physics and mathematics grades at university level. Differently, Smith and Peterson (2007) tested whether general or specific class-related advice would predict academic performance in an upper-level undergraduate lecture.

Social network theory utilizes three basic elements: actors or nodes; ties, edges or links between actors; and graphical representations of networks, which display the pattern of actor-to-actor relations using straight lines or arrows Putnik et al. (2016). Moreover, and depending on the context, nodes can represent subjects, organizations, academic departments, websites, or similar entities that are connected to each other within relatively fixed contextual boundaries Borgatti et al. (2013); Grunspan et al. (2014). For instance, in a classroom or school, each student might be perceived as a node, and the social relationships they declare with friends, lab partners, etc., constitute the social ties that would give life to the graphical representation of the network. Similarly, if one were to explore the level of interdisciplinary collaboration across a university campus, we could select academic departments as the nodes in the interdisciplinary network, and the number of projects and research publications where more than one department has presence, as the link connecting the referred nodes. Furthermore, the nature of these links is diverse depending on the research goals. Some of these categories are co-occurrent (e.g., group membership), social relations (e.g., knows, dislikes), interactions (e.g. transactions, activities), and flows (e.g., information, diseases). Most of the studies reviewed for this paper conduct SNA from interactions, like working together when solving problems (Bruun and Brewer, 2013).

It is important to note that nodes have characteristics or attributes. The nature of these attributes will vary with the nature of the node, like age, political affiliation and tenure are possible characteristics associated with individuals, whereas number of full time researchers, grants and papers published per year might be useful features of academic departments if the goal is to explore interdisciplinary collaboration.

Furthermore, SNA provides useful theoretical and methodological conceptualizations to understand social systems that traditional methodologies do not. Standard statistical method (i.e., T-tests, ANOVA, EFA, etc.) used in social science tend to group students based on psychological attributes or performance, overlooking the effects of social relationships under the assumption that students responses are independent from one another Borgatti et al. (2013). However, SNA takes advantage of the lack of subjects' independence (or high interdependence) and uses relational data as the basis for explaining the emergence of social structures, whether as product of contextual and/or shared attributes, or to explore whether these structures would influence the adoption of attributes and behaviors that might shape outcomes (Gaševic et al., 2013).

2.2.2 Basic Principles, Characteristics and Measurements

The literature in SNA differentiates two types of networks: unipartite or one-mode, and bipartite or two-mode networks. The former, one-mode, refers to set of relationships between a group of similar actors (e.g., students, teachers, faculty, organizations, etc.), and thus provides information regarding who is connected to whom in the case of individuals, without adding information about personal attributes, like performance, group membership, gender, etc. In contrast, two-mode networks will connect actors with their respective attribute information. Here, direct links between nodes are not directly measured, but are later determine on the basis of shared attributes, like group membership, gender, age, differences, etc. In addition to the graphical representations, it is possible to conceptualize networks using matrices. One-mode network corresponds to symmetric N x N matrices, where N is the number of nodes, whereas two-mode networks are not necessarily symmetric, thus taking the form of N x A, where N is the number of nodes, and A the number of attributes. Further, through simple matrix algebra it is possible to transform two-mode networks into one-mode, for instance to identify pattern of nodes that share (and not) the attribute measured in the two-mode network (Borgatti, Everett and Johnson, 2013).

In addition, whether ties are declared undirected or directed would have important implications on how relationships are described and effects interpreted. Undirected ties reflect symmetrical relationships between two nodes, such as if subject A states that she has played basketball with B, it would be fair to assume that B has also played with A. In the case of directed ties, these reflect unsymmetrical or hierarchical relationships, which would reflect implicit or explicit degrees of power within the social structure. For example, subject A admiring B does not necessarily means that the admiration is reciprocal. Further, the scores associated with social connections would reflect whether ties are binary or valued. Binary ties are used when researchers are interested in determine whether ties exist among a set of actors or not, that is, 1 for existing ties and 0 for the opposite, a practical decision for interpreting more complex network variables. Yet, by assuming that all existing ties in the network are equivalent in intensity oversimplifies the nature of the social systems. For this reason, allowing ties to be valued beyond 0 and 1 would add pertinent qualitative information, like frequency of interactions, meaningful or superficial friendship, etc., (Grunspan et al., 2014). According to Granovetter (1973), 'the strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie' (p. 1361). Consequently, the use of valued links among subjects might very well be perceived as tie strength, but with the condition that the network survey provides clear qualitative descriptions for the different response categories, for subjects to appropriately project their socio-emotional experience of interacting with others. Differently, Liccardi et al. (2007) reviewed studies where strong ties are defined as any direct link between nodes in a network, whereas weak ties reflect relationships of two nodes linked via a third one.

Studies in science education have used both types of tie categories (i.e., directed-undirected and valued-binary) to explore different social phenomenon. For instance, Reding et al. (2017) used non-directed and valued ties to investigated the amount of supportive ties female participants (age 12-14) developed through a 4 weeks summer program with undergraduate STEM students, who performed as scientific leaders. Moreover, Bruun (2014) used directed and binary ties to explore the conditions under which first year college students form their respective networks. Finally, whether researchers would use the different combinations of binary or valued, and undirected or directed ties would highly depend on the research questions and set of explanatory assumptions they attempt to test.

SNA researchers use multiple network measurement to characterize complete social structures, or whole networks. The boundaries upon which researchers define the social structure highly depend on the research context and questions. The most common concept and metric used to describe networks is cohesion, or the level of connectedness or 'knittedness' present in the network. Borgatti, Everett and Johnson (2013) combined a family of mathematical concepts to explore network cohesion. Cohesion is perceived as who is connected to whom, which in most cases is a consequence of homophily, the proclivity to connect with similar others (McFarland et al., 2014). Among these concepts, the most basic one that helps characterize cohesion is density, defined as the proportion of observed number of ties and the total number of links that would exist when all actors are tied to each other. Another popular cohesion metric is average degree of the network, which consists of the average number of connections observed by nodes within the network. From the research literature reviewed, network density has been used to test changes over time (e.g., prior and after instruction) as a measurement of students' engagement and participation (Brewe et al.; Reding et al., 2017). According to research-based results, positive changes in density measurements indicate an improvement in the number social relationships subjects declare, and interpreted as gaining access to 'features of social organization, such as networks, norms and trust that facilitate coordination and cooperation for mutual benefit' (Putnam, 1995; p. 67), or social capital (Gaševic et al., 2013; Rizzuto et al., 2009). In addition, there are other metrics that would also allow network characterization, like reciprocity (i.e., proportion of number of reciprocated ties and total number of ties in the network), or transitivity (i.e., friends of my friends are my friends), which leads to close triads. For obvious reasons, both reciprocity and transitivity are appropriate for directed networks. Due to length considerations, other whole networks metrics are not presented here, but are available in Borgatti, Everett and Johnson (2013) Chapter 9.

Differently from the mentioned whole network metrics, one may also understand networks by focusing on actor-level characteristics, like network centrality, a family of metrics sometimes associated with social capital (Borgatti, Everett and Johnson, 2013). These centrality measures vary depending on whether ties are directed (vs. undirected) or valued (vs. binary). For instance, in the case of undirected and binary ties, degree centrality measures the number of ties associated to a node, thus suggesting the actor's level of embeddedness in the network. A similar concept is betweeness, which measures whether the focal node bridges connections between other actors, by counting the proportion of shortest paths (i.e., geodesic distances) where the focal node is in between. Nodes that show high betweenness centrality are interpreted as having certain control over the communication between nodes (Freeman, 1978). In the case of directed networks, the centrality definition is extended to account for the number of ties that are directed from the node to the network (i.e., outdegree), and the number of ties that are directed from the network to the focal node (i.e., indegree). These centrality measures provide a better description of how socially active and participative subjects are in their respective social contexts. Moreover, closeness centrality indicates on average how close a focal node is to all other nodes in the network, measured through geodesic distances. Closeness centrality is an appropriate measure for non-directed networks, but similarly to degree, directed networks differentiate in-closeness and out-closeness. Consequently, and based on the mentioned centrality measures, and others not described here, actors with high centrality would have greater number of ties, probably connecting nodes that are not linked to each other, thus bridging structural holes (Burt, 2004), which would conduct them to access non-redundant information from different and unconnected sources. Compared to peripheral actors, people who enjoy central and brokerage positions within their network are positively associated with benefits such as promotion (Burt, 2005), innovation (Burt, 2004; Ibarra, 1993; Tortoriello and Krackhardt, 2010) and creativity (Sosa, 2011).

Science education researchers have used centrality measurements to explore whether the mentioned advantages of central positions transfer into classrooms and predict academic performance, retention, and self-efficacy. For example, Putnik et al. (2016) found meaningful correlations between centrality measures (degree centrality, betweenness centrality, closeness centrality, eigenvector centrality and average tie strength) and engineering students' performance, involving quality, volume, diversity of work and final grades. Similarly, Bruun and Brewer (2013) used different centrality measures (PageRank, Hide, Target Entropy, Indegree and Instrength. For a formal definition of these metrics, see Bruun and Brewe, 2013 Appendix), and FCI (Force Concept Inventory) scores as predictors of grades on two subsequent courses (i.e., Newtonian Mechanics and Linear Algebra). Later, Zwolak et al. (2017), explored the predictive nature of centrality measures used by Putnik et al. (2016) to test the predictable power of social integration on students' retention. Similarly, Zwolak et al. (2018) followed the same set of procedures to explore the influence of out-of-class relationships on persistence in future physics courses. Moreover, Brewe et al., took a different approach, and used indicators of participation on a Physics Learning Center (PLC) to predict future centrality. Their findings suggest that subjects have certain degree of control over their centrality in the learning center, where they collaborate with others with diverse levels of expertise, developing and validating models through participation in inquiry labs, and problem solving.

Finally, data collection and the instruments used for this purpose depends on the research questions and social context. There are two main forms of self-reported network survey: ego-centric and census networks (Grunspan, et al., 2014). Ego-centric surveys focus on the social ties of a sample of individuals, the 'egos', selected within the network boundaries, who are asked to provide the number, nature (e.g., friend, colleague) and/or attributes (e.g., knowledgeable in physics) of their relational partners, called 'alters'. In contrast, census-network or whole networks aim to explore the social ties of the population from a bounded social context. Moreover, these type of surveys can be administered through open-ended formats, where respondents write the names and nature of their relationships, or by selecting subjects from roster with the subjects in the population, with whom they may be linked (Borgatti, Everett and Johnson, 2013).

2.2.3 Benefits of SNA

As mentioned earlier, compared to traditional methodological approaches that rely on the assumption that individual responses or scores are independent within the sample, a social network perspective addresses the reality of social systems by understanding that individual behaviors and attitudes does not emerge from isolation, but most likely as consequence of social interactions. Therefore, SNA affords researchers a social perspective for a better understanding of subjects' experiences within the research context, and mechanisms to explore whether the social structures where individuals are immersed deliver social advantages. For instance, learning outcomes measured in traditional test formats, like standardized instruments (e.g., Force Concept Inventory), provide appropriate data for conducting standard statistical procedures, given that scores are assumed to be independent. Accordingly, knowledge is assumed to emerge only through student-material interactions, and far from the influence of any social relationship. However, and because learning outcomes are highly affected by social interactions (Liccardi et al., 2007), an SNA would use the data collected on standardized testing as individual attributes, to then measure an appropriate social network (i.e., advice and/or friendship network), from where it would be possible to explore the possible influences of social interactions on test performance.

Moreover, SNA allows education researchers to use constructs to define assessments and performance beyond individual test scores. For example, the study conducted by Goertzen et al. (2013) intended to understand social experiences in physics courses, drawing information on the constructs and characteristics that would allow students to become proficient physics students. More importantly, success is only not only determined by final grades; three additional markers contribute to defining success: changes in attitudes, ties within the physics classroom, and relationships within the larger physics learning community. Accordingly, the authors suggested that social interactions, roles and the behaviors students engaged in with the learning community (i.e., classroom) are necessary elements for the expected intellectual outcomes, if one were to evidence attitude change. In detail, when learning is seen as co-occurring in the different ways subjects interact with the community, then it is suggested that students experienced a change in attitudes towards the content, and behaviors associated with being part of that community, to the extent that it might defined identity. In networks terms, physics identity is developed when subjects are highly embedded in the learning community (i.e., high centrality), developing relationships with a vast majority of their peers. The usefulness of this approach extend itself from pure research purposes, and proposes an integral assessment philosophy from where to decide on best teaching practices

Furthermore, not only would individual performance be more comprehensive with the inclusion of network centrality measures, but SNA would also afford mechanisms to assess teaching practices and methodological innovations, based on whether whole network or actor-level metrics positively or negatively change over time. SNA adds interesting tools to test the learning and social effectiveness of methodological interventions, based on the benefits of social capital and its positive influences on performance and learning (Gaševic et al., 2013; Reding et al., 2017). Consequently, new pedagogical practices should boost social relationships, and encourage students to control who they collaborate with and learn from. Compared to traditional research methods for testing methodological interventions, which highly depend on standardize tests administered before and after instruction (i.e., pre and post-test), SNA facilitates the measurement of social structures, positions, and visualization of subjects' interactions throughout the intervention, along with the inclusion of individual or group-level attributes (i.e., test's scores). A study conducted by Brewe, Kramer and O'Brien (2012) adopted the mentioned perspective to test the effects of Modeling Instruction (MI) teaching methodology in students' participation and engagement in physics education. MI model is described as an active learning environment where students are encourage to participate in the construction of their knowledge, and likely to experience the value collaboration with other members of the learning community, based on the premise that students must engage in ways that mimic physicists' practices, hence working towards developing physics identity. Findings show a significant increase in network density after the implementation of Modeling Instruction, and similar significant differences were found between the experimental and a lecture-based group, suggesting that the active learning environment (Modeling Instruction) is a better pedagogical method for promoting a sense of community, and possible physics oriented identity.

Relative to the evidence presented so far, SNA can orient its efforts to determine the contextual conditions or attributes that trigger the creation of relationships. This is a unique research goal provided by SNA. Again, the principle of independence under which traditional research methods are constraint to perform, makes it impossible for the exploration of tie formation. Further, there are clear distinctions between utilizing contextual and individual attributes to explain tie formation. An example of the former would be the effects of Modeling Instruction in community participation (Brewe et al.). In a different study, Bruun (2014) studied the conditions under which networks are formed among first year college students, based on their experiences solving physics problems. Even though the study does not explicit personal characteristics, authors argue that group formation and segregation are consequence of having either positive or negative social experiences solving problems. Differently from the mentioned research possibilities associated with SNA, Forsman et al. (2014) suggested a novel approach to the study of students' retention from the perspective of complex thinking. Here, instead of using students as nodes, researchers focused on tests items, in an effort to determine item-level network metrics (i.e., centrality), and whether patterns of responses can be perceived as 'communities' with underlying similarities. The analogy with factor analysis and latent constructs seems evident, however, the perspective of complexity systems perceives the space of latent factors as a decentralized complex network, where the group of items that will defined these constructs are now conceptualized as the nodes in the network. Yet, these communities of items are in itself complex systems. To illustrate this, Forsman et al. (2014) used items taken from student integration (Tinto, 1997) and attrition models of persistence (Bean, 1982), plus other student-specific information and conducted exploratory factor analysis with responses from physics undergraduates. Items with high loading unto more than one factor are interpreted as neighbor interactions between the nested networks of items. Later, analysis of these factors allowed researchers to check clusters' proximity, or relative closeness, and differentiating between cluster and item-level centrality. Consequently, a similar interpretation holds for factor (i.e., clusters of items) and item-level centrality, both perceived as entities that maintain the decentralized complex network connected. Yet, identifying central items within and between factors might be important for different reasons. From a measurement perspective, factor analysis will stress that 'good' items should load highly only onto one factor, thus suggesting that the questions must trigger responses in the domain of the latent construct for which it was designed, and not others (Bransford and

Stein, 2015). Consequently, central items within each factor system (i.e., network) are perceived precisely as that, as 'good' measurement items, however, items with high centrality between factors, or central in the network of latent constructs, instead of being discarded for their lack of measuring 'quality', these could provide interesting insights to understand the functionality of the whole system.

2.2.4 Limitation of SNA

The main limitations of SNA are results of the assumptions under which researchers conceptualize social ties, which may affect reliability and validity of the survey instrument. One important concern relates to network boundaries, that is, the task of bounding the research context and defining the subjects that would be appropriate for the study (Borgatti, Everett and Johnson, 2013). Both decisions will depend on the research questions to be explored. In the case of school networks, the boundaries of the social network (e.g., classroom) would depend on whether the focus is on student-to-student, students-to-teachers, or teacher-to-teacher connections. More importantly, the nature of the link would vary depending on the nature of social ties one attempts to study (e.g., friendship, advice, admiration, in-class interactions, etc.). An appropriate network survey design would diminish potential misinterpretations of the social connections wanted, thus reducing error.

Moreover, whether researchers are measuring egocentric or census networks, there would always be problems associated with subjects' ability to recall past interactions, and even more if they are asked to make qualitative distinctions over these interactions (Bruun and Bearden, 2014). Research has found that students tend to remember more useful rather than less useful interactions in problem solving (Bruun and Brewe, 2013), but also their friends rather than peers who are located physically near them

(Eagle et al., 2009). Under this conditions, one should be aware of possible subjective bias, where relationships might reflect friendships or people that are liked rather the ties wanted (e.g., advice seeking). Even though one may consider both networks as highly correlated, these do not necessarily inform the same processes. Moreover, in some research scenarios where the focus of conducting SNA is to track the social influences on idea-generation and knowledge developed, one may feel tempted to directly ask frequency and from whom participants received valuable and appropriate information. However, Borgatti, Everett and Johnson (2013) suggest that because flow ties are difficult to obtain, it is assumed that through social relationships information is shared.

In addition, missing data is normally associated with network boundaries misspecification (Borgatti, Everett and Johnson, 2013), which might leave key actors out of the study, and thus miss important social interactions that would allow a better understanding of the social system. For instance, by paying attention only to student-to-student ties in a classroom setting, research might lack information on key interactions that may have happened between students and teachers (Grunspan et al., 2014). Similarly, the dynamic nature of social relationships (i.e., networks are not necessarily fixed in time) may add some limitations in data collection, as participants may shift their investment for relationships with individuals outside the boundaries of the network under study or alternatively, leave the social system. This is particularly challenging for census networks on longitudinal studies, as these demand larger samples with at least two times of data collection.

2.2.5 Conceptualizing School as Network and Implications

Perceiving schools and classrooms as social networks implies acknowledging the social dimension of the educational experience that involves multiple actors (i.e., students, teachers or instructors, parents, etc.). This conceptualization encourages the understanding that intellectual and psychological development entails a great social component that is worth paying attention to. A network perspective would facilitates mapping the school's and classrooms' social structure at different levels, and use it as a lens from where to explore educational experience, taking in consideration that curriculum, assessments, and the local culture of the school or university which might guide students social activity, its purpose and the benefits they may expect from these relationships. With this, my attention is back on the two main research purposes for conducting SNA: 1. Determine contextual and nodal attributes that ease tie formation; and 2. Explore how emergent structures and social positions shape outcomes. Next, I take each of these research directions and argue what it means to understand schools as social networks, and the practical implications of doing this.

Relative to individual characteristics that motivate the emergence of ties, the literature in SNA applied in education has investigated the effect of micro-mechanisms related to individual attributes or perceptions that influence tie formation (Biancani and McFarland, 2013). So far, research has characterized adolescent social structures based on their ability to find trustworthy others with whom individuals feel comfortable (conformity), or that express familiar behaviors and attitudes (homophily), or by developing hierarchical relationships (distinction of status) (McFarland et al., 2014). Each of the latter micro-mechanisms for tie formation reflects the extent to which individuals project their attributes into the social space, aiming to get an appropriate reading on whether other actors project the same behaviors and attitudes in the case of conformity and homophily, or different ones from where to select weaker or stronger peers. From this, it would be reasonable to suggest that individuals would engage in any of these micro-mechanisms to develop networks, in an effort to gain social support or access to social capital (Reding et al., 2017), with the consideration that this benefit could be understood as the projection of students' interests and expectations in the context of the social system. Moreover, conceptualizing schools as social networks implies a responsibility of understanding these attribute-driven processes of tie formation in and out of classrooms, and the extent to which the culture of the schools promotes either hierarchical or familiar relationships.

Based on the latter information, McFarland et al. (2014) tested an interesting model to explain the reasons why micro-mechanisms of tie formation are not context-invariant. The authors reviewed three environmental features of schools and classrooms that shape generative network processes: demographic composition, structure of instruction, educational climate, and included a fourth contextual dimension consisting on population size. In detail, based on demographic composition, shared attributes in highly homogenous networks is unlikely to become an important basis for segregation or the emergence of hierarchical structures, given the low number of categories for clustering. Consequently, the authors argued that increments on social heterogeneity would foster tie formation for conformity and distinction of status. Later, the structure of instruction refers to how students are grouped for instruction, or whether they experience selective or elective differentiation. While the former refers to school deciding to separate students by age and grades, the latter allows students decide based on personal preferences. Both contextual features guide to segregation and clustering, but through different mechanisms: by school definition of tracks based on achievement level, age, etc., or by student self-selection, or shared external attributes. In terms of educational climate, authors considered average levels of academic orientation (e.g., students display motivation towards acadmeic performance)and school attachment to operationalize whether students shared a collective identity associated with the school. Finally, classroom and school size would affect freedom and uncertainty in finding secure links with perceived trustworthy others. Here, freedom and uncertainty are inversely related as function of group size. Taking all these contextual features together, the authors defined a continuum that ranges from external identity exclusion, to external identity inclusion. The former reflects a school's culture with high number of constraints in the form of formal organizations, which would reduce liberties for students to form relationships by highlighting attribute homogeneity. In this scenario, micro-mechanism for tie formation are restrained, given that decision for network formation are taken at an organizational level. Conversely, external identity inclusion arises in open settings that impose few constraints on interactions, with reduced formal organization, and are based on more elective than selective grouping decisions (e.g., college and universities). This leads to higher levels of heterogeneity and uncertainty, which ends up amplifying tie-formation mechanisms leading to segregated and hierarchically clustered networks of relations.

Moreover, it has been established that certain social structures and networks positions are privileged for accessing academic resources and supportive social ties that would affect outcomes (Gaševic, Zouap and Janzen, 2013). Consequently, school decisions and actions made for the sake of improving academic outcomes should be taken with the consideration that these will have effects over the mechanisms students use for social segregation and clustering. This led to the conceptualization of pedagogical innovations not only from the expected benefits on knowledge development, but from a more integral viewpoint that demands addressing possible negative and positive effects of the innovation on the formation of social networks. This perspective somehow drives a shift in the focus of decision-making at school, from the expected learning outcomes, to the expected social structure that would facilitate knowledge building and skills. Accordingly, conceptualizing schools as networks involves emphasizing the importance of network formation in the learning process, and accepting the reality that some social structures are key for knowledge development (e.g., Bruun and Brewe, 2013), persistence in school (Forsman et al., 2014; Williams et al., 2017; Zwolak et al., 2018, 2017), and self-efficacy (Dou et al., 2016). Finally, and from a pedagogical perspective, the question that arises from the research evidence is whether these social structures facilitate good performance across different learning activities, or whether there are benefits that come from isolation versus being embedded in a learning community. It may be fair to think that some learning activities would benefit from the information flow afforded by social ties, respecting the mechanisms associated with creative combinations (Burt, 2004), yet, there may be others where students would benefit from only a few ties, regardless of their position in the overall classroom structure, engaging on reflections over a well-bounded content that all actos in the cluster have access too Rhee and Leonardi (2003).

In addition, a network conceptualization also suggest including social perspectives for assessment purposes, stressing the importance of participation and engagement in the learning process. Rogoff et al. (1996) operationalized learning as a change in participation, and was later used by Goertzen, Brewe and Kramer (2013) as the theoretical lens to test whether students develop a identify through engaging in the community. Although this participationist conception of learning does not replace individual performance on standardize testing or other learning activities, it provides comprehensive information to understand students' performance as influenced by social structures. Moreover, having access to a snapshot of the class network with academic performance as individual attributes, would facilitate the recognition of weaker and stronger students, and the positions they use. But more importantly, a network visualization may offer directions for future strategies oriented to ease knowledge transfer and foster learning, specially focused on weaker students, who most likely would occupy peripheral positions within the network. The latter replicates the philosophy of assessment, by perceiving this practice not as an exclusive moment for ranking students, but as an opportunity to collect information on students' progress, that would inform and influence decisions on how to improve instructional and pedagogical strategies.

For obvious reasons, there are practical issues associated with conceptualizing schools and classrooms as networks, and pursuing the goals mentioned above. These issues replicate the steps required to conduct SNA. First, teachers and school professionals will have to make clear what types of networks matter in the school context, and its boundaries (e.g., classroom, grades, floors, etc.). If the classroom network is the focus for understanding students' participation, the data must be collected at several time points, and across multiple classes. Yet, including data collection for mapping social networks could be time consuming. The easiest and fastest way for doing this seems to be self-reported data through paper and pencil or online surveys. There are also qualitative methods based on video recording that could be useful as well, but might demand more time as these methods require operationalization of interactions, and further coding (Pomian et al.).

2.2.6 Important Networks in Education

It is worth remembering that most network data is collected through survey questions defined to elicit a particular social relationship. (e.g., learning peers, communication, etc.), which are associated with particular actions, contexts or social benefits. Importantly, these social ties must be presented through detailed qualitative definitions expected to reduce potential misinterpretations. Consequently, before deciding from a universe of multiple tie categories that might develop and/or explain outcomes, it would be essential to identify the potential benefits or lack of thereof, for gathering information on a given set of relationships with others. For instance, Dou et al. (2016) used egocentric data and asked students to name peers with whom respondents had meaningful interactions in the classroom on the day of data collection. Goertzen et al.

(2013) used a slightly different ego-driven method and asked subjects whom they worked with to learn physics. With more detail, Bruun and Brewe (2013) collected relational data by administering weekly questions on three different (but related) tie categories: 1. Problem solving: social interactions in the context of solving physics problems; 2. Concept discussion: social interactions around conceptual understanding of physics; and 3. In-class social: or interactions of different nature associated with solving problems, lectures, or lab sessions. The mentioned survey questions and the categories of interactions these attempt to measure are relatively similar, and all associated with learning partners in the context of a physics class. The interesting differentiation of the learning processes in physics education made by Bruun and Brewe (2013), can provide insight into whether the class network withstands the cognitive requirements that problem solving and conceptual discussions entail. Therefore, in the face of each of these cognitive tasks, students may direct their attention to different resources in the form of social ties, and develop 'task-specific' relationships by either reaching out more (or less) capable physics students (i.e., hierarchy), or those with whom they feel comfortable working (i.e., conformity), or those that shared similar attitudes and behaviors (i.e., homophily). Differently, Rienties and Kinchin (2014) combined learning ('I have learned from...'), and working ties ('I have worked with...'), with friendship (I am friends with...), to explore the extent to which teachers in a professional development program created communities to effectively learn together. Including friendships in the mix of networks may provide information on ties that go beyond the formal boundaries of a program, classroom or teams, which may connect two or more of these formal settings. In the case of classrooms or defined learning groups, friendship ties would inform on whether individual social networks span outside the limits of the formal clustering organization, adding valuable insights for understanding diversity of knowledge, experiences, behaviors, within the formal network. Moreover, this forces researchers to differentiate ties within (internal) and between (external) formal networks, and recognize the importance these external connections may have on learning and the emergence of good ideas. Subjects connecting formal groups (i.e., external ties) are associated with knowledge spillovers or boundary spanners (Burt, 2004), a role that is perceived as bridging previously unconnected sections of the social network, thus allowing for non-redundant (i.e., novel) information and ideas to flow in both directions for social and/or intellectual benefit. With this information in mind, it is clear that schools and university classrooms would benefit from mapping learning and work-related interactions, along with friendship, assuming that knowledge, attitudes and behaviors flow through these relationships influencing how subjects, in this case students, experience being social members in school. Importantly, I recognize that gaining access to students' interactions is challenging, and that information flow is a hidden goal in the network survey design, in the sense that one must assume that friendship and working alongside other facilitate access to information.

2.2.7 The Effect of Network Structures on Learning

The research literature of SNA applied to educational contexts has provided interesting results on the networks positions and structures that are most effective for academic purposes, particularly centrality and density. In simple words, academic success is a consequence of who you know, rather than your isolated knowledge. Academic performance is most likely to be enhanced by being immersed in a dense network (i.e., where nodes are highly connected), from which students can take advantage of the information, skills, abilities others might share through social ties (Gaševic et al., 2013; Smith and Peterson, 2016). Rienties and Kinchin, (2014) reviewed four reasons that explain the positive effects accessing the resources embedded in a social structure, or social capital. First, resources rooted on the social systems are less resistant to flow between actors, easing transaction costs, and therefore encouraging collaboration. Second, embeddedness in the social system reflected in a high number of ties with actors of diverse power might influence organizational change. Third, network connections may be perceived as evidence of social power, given the high access to resources available, and the possibility to affect the system's future. Finally, embeddedness in social networks implies psychological and emotional support that might lead to identity.

Moreover, network centrality has proven to have similar effects on school performance and persistence than density, yet the latter has been less explored, relative to the literature reviewed here. For example, high degree centrality in undirected networks reflects a great number of relationships with others, relative to the number of possible connections, but assuming reciprocity. More detail in the network is gained from indegree (i.e., ties directed to the focal node) and outdegree (i.e., ties directed from the focal node to the network). Indegree could reflect popularity or power, whereas outdegree may be interpreted as social engagement and active participation. Similarly, actors that show high betweenness centrality have certain degree of power over the information that flows between nodes (Freeman, 1978). Most of the studies cited here explored relations between network metrics and academic outcomes using these and/or other centrality measurements (e.g., eigenvector centrality, closeness, average tie strength, etc.) (Grunspan et al., 2014; Putnik et al., 2016; Bruun and Brewer, 2013; Zwolak et al., 2017; Smith and Peterson, 2016). The positive research-based evidence found on network centrality and academic performance aligns with benefits of network embeddedness for social capital.

Knowing the importance of network density and centrality in knowledge building and school experience, is a first step to staring to think about the types teaching strategies, or school-level decisions that would be most appropriate for taking advantage of the influence of social relationships. To do so, it is worth recognizing that the benefits of social capital are grounded on two interconnected dimensions: accessing to unique and diverse source of information, advice, etc.; and social prestige and power. Because it appear that prestige and power are likely to come from having the ability to establish relationships with others who represent unique and diverse sources of information, appropriate network structures must favor the existence of knowledge diversity within its domain. Without knowledge diversity within the network, one could assume the unique scenario in which it would not matter whether an actor is a central or a peripheral member of the network, as new information will not enter the system (i.e., knowledge redundancy), thus, limiting social mobility motivated by intellectual growth or social prestige. This case would represent a flat network with no hierarchical distinctions (McFarland et al., 2014), and no differences between central and peripheral subjects in terms of (lack of) social capital. A classroom setting in which all members have similar background knowledge, skill sets, and are connected to each other (i.e., high network density), but with no formed relationships outside the classrooms for an inflow of novel ideas may constitute an appropriate example, or whether the content is well-bounded and accessible to every member.

In the opposite case, diverse knowledge (i.e., non-redundancy) and skills scattered over the network would motivate social movement, because subjects would have to engage and invest in their respective social systems in order to access actors and information from where they might get intellectual benefits, and ultimately social prestige and power. In this case, each node within the social network is weighted according to perceived knowledge attributes and social influence. Consequently, hierarchical classrooms will have students, or groups of students, with diverse background knowledge and experiences that might be perceived as having resources available to use within the network. In this context, a resource can be understood as any novel strategy, idea, experience, etc., learned or accessed through formal, informal, internal or external ties (Rienties and Kinchin, 2014). Students located at central positions would enjoy the benefits of social capital by having connections with multiples actors who may or may not be connected to each other, thus accessing sections of the network that provides both redundant and non-redundant information. This scenario does not only predict learning, but also innovation (Burt, 2004; Ibarra, 1993; Tortotiello and Krackhardt, 2010) and creativity (Sosa, 2011).

Further, it is undeniable that classrooms are defined under a unique curriculum and learning objectives that all students are expected to meet at the end of the academic term. Although this fact could be perceived as an argument against the possibility of having diverse knowledge inside the classroom, this should not be confused with the attitudes, behaviors and knowledge that students developed through prior experience or external ties and bring to the social network in the form of resources. Knowledge diversity and perceived resources would then contribute, through social ties, to the multiple ways in which subjects would build understandings and produce outcomes regarding the common learning goals, with the consideration that students must engage in effective forms of communication in order to access and take advantage of such resources.

Taking into consideration the influence of social structures and positions on subjects' learning experiences, it may be worth paying attention to the mechanism and decision that would boost the benefits associated with social capital. The micro-mechanism used for segregation and clustering (i.e., conformity, homophily and distinction of status), would be perceived at different degrees depending on whether subjects in educational settings engaged in external identity exclusion or inclusion (McFarland et al., 2014). In simple words, these differences would reflect the extent to which schools and classrooms are heterogeneous, where students shared a sense of identity and attachment, as well as opportunities to decide which classes to take. In relation to the positive effects of hierarchical structures associated with non-redundant information and social capital, it seems reasonable to suggest that a combination of organizational decisions that facilitate liberty and heterogeneity (i.e., external identify inclusion) would be preferred if the goal is to encourage intellectual and social growth. Yet, in the case where these organizational conditions orient to exclude rather than include individual identities, teachers and instructors may administer and design learning activities and instructional strategies that encourage social clustering and segregation, but for the right reasons: to mimic hierarchical social structures that boost social capital, but within the limits of the classroom. For instance, Rienties and Kinchin (2014) suggested the positive effects of boundary spanning activities where individuals from different groups interact with the goal of gaining novel information. Under this type of activitiy, and depending on how diverse the knowledge is spread throughout the network, group density and heterogeneity would play an important role in translating and transforming the knowledge transferred from these bridging connections Akkerman and Bakker (2011), in such a way the focal group is able to utilize the new information for its own benefit. Accordingly, Liccardi et al. (2007) reviewed research evidence in group performance, and found that social learning was stronger in groups with high social identity, hence, supporting the strategy of group formation, and the integration of teams within the social network for better learning outcomes.

2.3 Group Creativity and Social Learning

The emergence of creative ideas and learning from collective efforts is a complex and social phenomena, with important implications for education and professional success. In this sub-section, I begin by defining group creativity in connections with the individual, group and social variables that may have an effect over creative performance. Finally, I explore the research approximations found in the literature for the study of group creativity and social learning.

2.3.1 Conditions for Group Creativity

Before attempting to define group creativity, it would be worth directing one's attention to the different levels where creativity operates: personal and group. Every creative idea emerges first at a cognitive level, mirroring what it is understood as deep learning, that is, the process of developing logical connections between prior and new knowledge, as a mechanism for human adaptability (Inhelder and Piaget, 1958). From here, individual creativity is conceived as a cognitive process that facilitates novel and appropriate understandings of reality, enabling subjects to face daily problems. Novelty and usefulness are two necessary conditions for creative ideas, or understanding in this case Amabile (1996). At the individual level, originality is relative to the subjects' experience, and one may assume that every time new information is attached to prior knowledge, the novel nature of that logical link meets the conditions for creative understandings (mini-c creativity). Moreover, the main goal of learning something is to develop a cognitive structure with appropriate and useful information that would enable individuals to face reality and its problems. It may seem obvious to state then, that the ability to be creative in a given field of knowledge reflects subjects' degree of expertise, to the extent that more and deepest understandings would provide a better base for the emergence of novel and appropriate ideas (Csikszentmihalyi, 2013; Runco and Jaeger, 2012; Sternberg, 2012).

An interesting model to understand individual creativity was generated by Kaufman and Beghetto (2009), and called Four C Model of Creativity, where creative ideas emerge in four different dimensions referred to as mini-c, little-c, Pro-c, and Big-C. At the individual or cognitive level, creativity leads to knowledge-building and understanding, as a product of novel and logical relationships between prior and new information. This mini-c creativity (Kaufman and Beghetto, 2009), is a dynamic process that facilitates novel and appropriate understandings of human experience, and can be transferred into real world contexts to address everyday activities (little-c creativity). In addition, when these creative ideas emerge to solve problems in professional settings, they are referred to as Pro-c creativity. In these cases, novelty is a characteristic experienced at individual level, however, Big-C creativity is an idea whose originality and appropriateness transcends the social context where it is created, and is accepted for a field of experts as creative. In the context of a classroom one would expect participants to engaged and experience the first two dimensions of this model, that is, mini and little-c creativity. The conceptualization of individual creativity as an approximation of individual learning is of key importance to further comprehend why group creativity can be a valuable lens from where to study collaboration and idea generation.

Thompson (2003) suggested that individuals excel at divergent thinking, whereas teams are better at convergent thinking, which sounds contradictory given the well-known assumption that teams should be better for creativity. In detail, and related with research included in this review, discussion groups are worse than individuals at brainstorming and generating novel ideas, because teams 'waste' time on necessary social process rather than proposing ideas. Yet, teams are most needed in selecting the right ideas to develop (Baruah and Paulus, 2008), which is fundamental for developing novel and useful solutions. Accordingly, creativity in isolation is unlikely to happen, and even when performance is individual, we should recognize the function of social and contextual factors on the outcome (Fleming et al., 2007; McMahon et al., 2016). In the context of groups, the emergence of creative understandings or ideas are likely a consequence of interactions between individual knowledge and new information received from the social context. This drives the differentiation between individual creativity in a group, and group creativity. The first relates to individuals facing a creative task as members of a group, where the group processes influence over personal creative thinking at cognitive and motivational level De Dreu et al. (2011). Second, there are not formal definitions of group creativity in the reviewed literature, but rather some studies provide certain assumptions or characteristics under which collective creativity is likely to emerge in different scenarios. Based on what the research field in creativity provides, group creativity could be understood as the set of processes individuals undergo while collaborating with others, in an effort to generate original and appropriate solutions (Baer et al., 2008; Baruah and Paulus, 2008; De Dreu et al., 2011). The underlying association between individual and group creativity lays on the fact that the latter is not possible without the former, which consists of a complex process that entails more than the additive function of individual performance, but rather group-level factors that may encourage or discourage team members from sharing what they may perceive as novel ideas (Taggar, 2002). According to the componential theory of creativity **?**, intrinsic and extrinsic motivation, domain-relevant skills, and creative relevant processes are consider conditions that would nourish creativity at individual level. However, team creativity literature would suggest that having a high presence of the latter characteristics distributed among members, is not enough for teams to engage in creative thinking and productivity. Moreover, group creativity would likely depend on team creative processes, defined as a function members engaging on mechanisms for connecting ideas from diverse sources, addressing new approaches, or novel ways of performing a task Gilson and Shalley (2003).

An interesting perspective of group creativity is provided by Sawyer (2003, 2006b), who explored the nature of creative collaboration in the context of music ensemble and improvisational theater. Sawyer's conceptualization of groups has its focus on how dialogues guide creative individual contributions that maintain the performance flowing. Accordingly, when groups collaborate with the goal of producing creative outcomes, participants' ideas emerge as product of interactions with what other members are saying and proposing in the form of constraints that direct the discussion (or performance) to certain direction. This constant interaction in the form of critique, assessment and development of ideas allows each member to build upon each other's contributions to generate a high quality performance. The extent to which individual ideas actually contribute to the creative performance would depend on whether these add valuable information to tackle the task the group is facing. From the work of Molenaar and Chiu (2017), who studied group creativity by paying attention to sequence of cognition, one may explore the relative value of an idea by focusing on whether a sequence of contributions entails high or low cognitions. This dichotomic process mirror mirror Bloom's learning taxonomy, with low cognitive processes associated with repeating or remembering the information that team member are stating, whereas higher-order processes imply generating new understanding and associations. In collaboration, the former process might consist of reading aloud and processing information from external sources, whereas the latter (i.e., high cognition) would refer to processes that enable construction of meaning, like asking on-task questions, generating new ideas, elaborating them, and critiquing. Consequently, one may determine that members would activate different set of cognitive processes depending on whether the information embedded in the contribution is perceived as valuable.

Later, Sawyer's (2003; 2006) theory included three valuable features to define group creativity. First, creative collaboration should not be reflected only in the group outcome, but rather in the processes that allow groups to produce original and effective solutions. In the context of music and theater, the creative process of improvising music or comedy becomes the ‘product’ that the audience wants and demands to see. Second, the emergence of creative ideas is unpredictable to the extent that the task allows creativity within its parameters. This guided Sawyer and DeZutter (2009) to conceptualize tasks in a continuum governed by the degree of unpredictability. In one extreme one may find highly predictable tasks, such as close-ended or well-defined physics problems, whereas the opposite end will include highly unpredictable activities with no embedded constraints. A predictable and constrained performance implies that the collective process is highly scripted, and members are expected to perform within the restrictions imposed by the context or situation. In contrast, unpredictable and unconstrained performances are located in the opposite end of this continuum, where there is room for whatever members seems plausible to do in order to succeed on the task. Because ill-structured physics problems emerge within a learning context, it is impossible for these to have no task requirements, and consequently, one may position them along the continuum close to unpredictable tasks. Steiner (1966) labelled well-structured problems as disjunctive tasks, because when engaged in groups this can be solved by the most capable member of the team and without the necessity of further discussion. Further, and even though some teams may feel comfortable by giving the most skill full member the liberty to decide on the solution, one would expect this ill-structured problems be solved as additive tasks, where performance emerged as the sum of all members’ contributions and relevant abilities.

Finally, Sawyer included intersubjectivity as a key element for the creative “synchrony”, similar to what Gilson and Shalley (2003) considered as team creative processes. In detail, Matusov (1996, cited by Sawyer, 2003, p. 9) claimed intersubjectivity as a “process of coordination of individual contributions to joint activity rather than as s state of agreement” (pp. 34). This group characteristic is of key important particularly for open-ended tasks, where the infinite number of possibilities demand an emergent collective coordination, first to provide meaning and sense to what others are saying and doing, and second, for the group to perform in flow and synchrony.

The research literature on creativity and innovation has been paying attention to the different set of conditions that enable teams and subjects to perform creatively. Based on this research evidence, it is possible to differentiate among individual-level and group-level features and processes that orient themselves towards creative outcomes, and the social structures and networks positions that facilitate the emergence of creative ideas.

2.3.2 Individual Conditions for Creativity

First, individual attributes and motivations for facing the task would play an important role in how group discuss and decide on the best ideas to utilize. The first obvious element that would play a key role in allowing creative outcomes is domain-relevant knowledge and skills (Amabile, 1996). According to the semantic network models, memory and knowledge is represented by a network of concepts, connected through logical associations between them, and distributed in such a way that nodes highly related will be located closer to each other. Under these conditions, ideas are generated depending on the activity of the regions where these are stored, and the external stimuli that would activate them. For instance, Johnson and D'Lauro (2018) argued that in the context of brainstorming sessions, ideas associated with dense sections of the network would come up faster, followed by less active or less dense cluster of concepts. This process will continue until there are no more active network areas from where to retrieve ideas. Because first ideas come from denser structures and have higher cognitive value (i.e., intellectually richer), then one would expect that these ideas would be of higher quality than the ones generated at the end of a brainstorming process. This is consistent with the importance of attention and concentration on the domain of knowledge upon which subjects direct their creativity (Csikszentmihalyi, 2013). Consequently, attention to knowledge (i.e., learning) would reflect the degree to which individuals are developing hierarchical networks of understandings, which would allow them to identify faster the key concepts to use when combining new information for creativity.

Further, intrinsic and extrinsic motivation are two important elements for sustaining the effort and persistence necessary for creative outcomes (Amabile, 1996). Along this line of thinking, the nature of the task, and whether subjects are capable of identifying themselves with whom might benefit from their performance would influence persistence, performance and productivity (Grat, 2008). In this context, the extent to which subjects are willing to help others is reflected in their prosocial motivation as a moderator of intrinsic motivation. Accordingly, when individuals show high intrinsic motivation, prosocial motivation is characterized by perspective taking, 'defined as a cognitive process in which individuals adopt others' viewpoints in an attempt to understand their preferences, values and needs' (Grant and Berry, 2011). However, with low intrinsic motivation, prosocial motivation is perceived as pressure to complete the task. Moreover, research evidence found by Grant and Berry (2011) supported the relationship between intrinsic motivation and creativity proposed by Amabile (1996), but added the moderating effect of prosocial motivation on intrinsic motivation, mediated through perspective taking.

Following with the individual factors that influence creativity, the Big-Five model (Gosling et al., 2003) of personality (extraversion, openness to experience, conscientiousness, neuroticism, and agreeableness), allows an interesting conceptualization of individual attributes that might foster or limit group creativity. In detail, research evidence proposed by Baer et al. (2008) suggest that groups are more creative when members show high levels of extraversion, openness to experience, and low levels of conscientiousness. Yet, these effects are strongly mediated by a team-level attribute labeled team creative confidence, which refers to a collective motivation and shared belief that the group performance would generate better outcomes than if individuals were to work by themselves. This team-level belief is most likely connected with subjects' motivation to collaborate with their teams, being this an alternative definition of prosocial motivation (De Dreu et al., 2011). This social motivation is grounded on the awareness that collective performance tend to be more productive and psychologically safer than individual efforts. Moreover, groups are found to be more creative only when members have high epistemic motivation (i.e., willingness to comprehend the reality that surrounds them) and are prosocially motivated (De Dreu et al., 2011).

2.3.3 Group and Social Conditions for Creativity

Consistent with Amabile (1996), having members with appropriate knowledge skills is a necessary condition for group creativity. Yet, too much expertise on a particular knowledge domain could push teams to pursue conventional routines to address the tasks, which might end up in limiting social interactions and group discussions, given that members would not experience the necessity of original approaches, nor the risks associated with them. For this reason, teams with diverse degrees of domain-relevant skills would require more socialization and group discussion, thus increasing the likelihood of engaging on creative processes (Gilson and Shalley, 2003). Similar to having a lack of diversity of knowledge expertise among members, a team's attraction, or the desire to be part of the group (i.e., cohesion) would have a similar negative effects over creativity (i.e., too much cohesion is detrimental for novelty) (Wise, 2014). Under this circumstances, Park et al. (2017) argued that groups with high team efficacy (i.e., members' belief of the team's capability of success), are likely to share beliefs about the team's competency, trusting too much in their own abilities, and overestimating the complexity of the task. Moreover, in teams of low efficacy, the underestimation of individual and group abilities is amplified by having high cohesion. In simple words, cohesion is a moderator in the relationship between team efficacy and performance, to the extent that moderate degrees of cohesion are wanted for better team performance.

The research literature on social networks and innovations has focused less on team level features, than on actors' structural positions within the social network, and the advantages these structures provide for creative recombination. Consequently, the emergence of creative ideas would depend on how information is transferred through social ties, from zones of high knowledge redundancy (i.e., high network cohesion), to zones of low knowledge redundancy (i.e., structural holes). Granovetter's (1973) theory of weak ties suggests that information is diffused faster and without much resistance through weak social connections, because these links are directed to actors who do not belong to the same cohesive group, and therefore are located in zones perceived as of low knowledge redundancy from the position of the focal actor. Consistently, actors who bridge connections between two unconnected pairs of individuals or groups, or who span structural wholes, would enjoy the advantages of social capital by accessing the resources available in the network (Burt, 2004). With this brokering effect, both networks may access non-redundant knowledge that would possibly enable creative combinations and further innovation. However, Hansen (1999) proposed that strong ties allow the social learning of complex, tacit or non-codified knowledge, whereas weak ties facilitate the transfer of simple or codified knowledge. This evidence implies that cohesive networks where actors are connected through strong ties would ease transfer of complex information, because the nature of their social relations would contribute to passing on common knowledge, norms and codes for communication, thus decreasing the competitive dimension of social capital, and motivating social learning (Reagans and McEvily, 2003). Conversely, the social investment required to transfer complex knowledge (e.g., time, energy and probably resources), would make it unlikely for this type of information to flow through weak ties.

The nature of the links (i.e., strong or weak ties) through which different information (i.e., complex or simple) can be learned is of key importance for predicting individual and team creative potential. Fleming, Ming and Cheng (2007) explored the dichotomy between cohesive networks and brokering knowledge (i.e., network range), but differentiating between generative creativity (i.e., creative recombination) and creative success (i.e., usefulness). As mentioned, being part of a cohesive network implies forming part of a cohesive cluster of strong ties where actors are likely to trust to each other, and share a fair degree of common knowledge (i.e., redundancy) and behaviors and norms that would facilitate the social learning of complex ideas. In addition, structural bridges connecting cohesive networks are likely to be weak ties that would ease the transfer of simple and non-redundant knowledge, ideal for creative recombination. However, generative creativity is not the end of the creative story. Even though brokering seems ideal for the generation of novel approaches for solving problems (Burt, 2004; Hardagon, 2002), developing creative ideas into real solution demands work and effort, a social investment that cohesive groups are more likely to take. Moreover, Fleming et al. (2007) determined that creative solutions tend to emerge and be developed by cohesive networks, where focal inventors and collaborators have broader experience, or have worked on diverse organizations. Members' prior experience somehow replaces the value of bridging structural holes, and adds the needed non-redundancy for generative creativity. In addition, and even though brokering increased the number of good ideas, these were not used with the expected frequency for the cohesive group. These results also suggest the distinction between generative creativity and creative arbitrage. While the former refers to the emergence of novel ideas by combination of conventional and new information, creative arbitrage is the process of ideas being exported to new contexts, where their originality and appropriateness is assess relative to the features of the task and actors' expertise and experience.

From the advantages of brokering new information from sparse networks, groups located in central positions of the networks are more likely to succeed because they are placed in paths connecting two or more teams, and therefore have access to the information that is transferred through those links (Tsai, 2001). In contrast, peripheral groups placed at the end of the information path depend on central groups letting the knowledge flow in their direction, and therefore, making them less likely to take faster advantage of the resources flowing throughout the social system (Dawson et al., 2011). Moreover, and because networks are dynamic systems that change through time depending on contextual demands, networks positions are not necessarily stable. With this, actors and groups have a certain degree of control over the role they engage in within the network, and thus can oscillate between periods of deep group commitment and high network density, to periods of brokerage or connecting groups across the network. According to Burt and Merluzzi (2016), this process of network oscillation poses certain social advantages, like fostering individual's local reputation in the different groups that he or she has engaged in, which may afford benefits when the actor oscillates from brokering and tries to introduce new ideas into the group. In addition, this oscillation could allow subjects to face a variety of knowledge and dynamic collective process, thus forcing them to establish strategies for adaptation, learning, and effectively respond to contextual changes, and finally, could improve social and intellectual benefits by simple allowing subjects to maintain larger and diverse networks.

The above evidence highlights the importance of social positions for idea recombination, however, Rhee and Leonardi (2003) found that highly constrained networks afford opportunities for creative ideas, but though different cognitive processes than actors who span structural holes. Accordingly, actors may take advantage of the highly constrained network when the attention to information is focused on a particular content and its related ideas rather than dividing their attention into the diversity of information flowing throughout the network. The mechanism through which this may happen was defined as interrogation logic (Rhee and Leonardi, 2018), and consists of deep examination of the local knowledge managed by the individuals embedded in the cohesive network. Because highly constrained networks are characterized by strong ties (Burt, 2004), it is reasonable to think that actors in such a structural situation would manage a common and well-bounded volume of information. Consequently, the strong ties that connect all members in this cluster may facilitate the collective questioning and reflection over the local knowledge, leading to the emergence of new and complex ideas, that are relatively easy to learn and develop through shared strong ties (Hansen, 1999; Sosa, 2011; Reagans and McEvily, 2003).

Consequently, individual and group attributes, as well as the social system where the team is performing would influence the likelihood for creativity. However, there are contextual factors and task features that might also encourage teams to engage in creative thinking processes. For instance, the extent to which endogenous dynamics (e.g., teams' unique sequence of processes) are in synchrony with exogenous time pressures, coming from the social context where the team is performing, and expectations would influence how individuals and groups utilize their repertoire of strategies and skills to perform effectively (Goh et al., 2013). Moreover, tasks should provide a fair degree of ambiguity and unpredictability for decision-making and creativity (Sawyer and DeZutter, 2009), that would encourage individuals' motivations to take action within their groups and their network. Importantly, Grant's (2008) perspective taking concept proposes a useful guideline for designing group tasks that might trigger effort guided to help others (i.e., prosocial motivation).

2.3.4 Research Methods for the Study of Group Creativity

There are two main methodological perspectives used to study group creativity and social learning: 1. Traditional qualitative and quantitatve methods, and 2. Social network analysis. First, I consider, traditional quantitative and qualitative methods. Quantitative approximation to group creativity consists of a combination of individual attributes and survey responses, which would permit conceptualizations of group-level attributes (e.g., team efficacy, team creative confidence) for predicting performance (Baer et al., 2008; Gilson and Shalley, 2003; Sitar et al., 2016; Taggar, 2002). Another set of methodological strategies has consisted of observations and analysis of groups' addressing the task and their outcomes, aiming to test predictions, or explore patterns of interactions and processes that would explain team performance (Goh et al., 2013; Johnson and D'Lauro, 2018; McMahon et al., 2016; Molenaar and Chiu, 2017; Sawyer, 2006b). The second research lens comes from social network analysis (SNA), which allows understanding social systems in terms of emergent structures and positions that would either facilitate or limit knowledge transfer for creativity (Dawson et al., 2011; Fleming et al., 2007; Leonardi and Bailey, 2017; Reagans and McEvily, 2003). In all these different scenarios, the task individuals and groups faced may be perceived as a contextual factor that triggers creative processes that researchers want to explore, whereas the outcome is the entity subjected to originality and feasibility.

From a quantitative perspective, studies have been consistent on their conceptualization of group creativity as an aggregated function of members' characteristics and abilities. For instance, self-reported personality traits and characteristics (e.g., Big-Five Personality model), can be aggregated as group-level metrics to either determine attribute's distribution within groups, or metrics of central tendency (Baer et al., 2008). Moreover, based on members' experiences with their groups, researchers are able to obtain approximation to team variables, like team creative confidence (Baer et al., 2008), creative processes, or the extent to which participants share, critique and decide on valuable information (Gilson and Shalley, 2003), and creative performance (Taggar, 2002). Later, the relationship between variables has been explored through standard statistical techniques like linear, multiple and hierarchical linear regressions, as well as structural equation modeling, all of which afford researchers, not only evidence direct associations, but moderating and mediating effects too. For instance, in the work of Sitar et al. (2016), creativity is predicted by both independent and collaborative learning styles, yet these relationships are mediated by self-efficacy and enjoyment respectively. In more detail, an independent learner would prefer to trust their own learning processes, skills, knowledge and strategies for achieving creative outcomes, whereas collaborative learners would enjoy working and learning with others, leading to higher levels of motivation, social processes and communication with people with different beliefs and background knowledge, enabling them to access valuable information for creativity. Further, the reviewed studies operationalized creativity in different ways. Baer et al. (2008) used novelty and feasibility as creative criteria to assess group outcomes, while Taggar (2002) operationalized creativity as a set of behaviors reported by team members (i.e., discovers novel relations using old concepts, and looks at the content from a different perspective), and Sitar et al. (2016) as a self-reported response to creativity questionnaire.

Quantitative methodologies for studying creativity and social learning have mainly focused on observing group processes in creative tasks, or their outcomes, or a combination of both. Observing how ideas emerge from group discussion is the main source of information in Sawyer's (2003) work, and the feature that he recommends investigating to grasp how collaborative creativity occurs. Similarly, Goh et al. (2013) explored team innovation processes, or cycles of planning, enacting and reviewing activities on project groups developing interactive media products. Using observation of team meetings as the primary source of data, that was later subjected to coding on the three activity levels: planning (i.e., related to future states or actions), enacting (i.e., direct references to task performance), and reviewing (i.e., reference to actions that were previously performed). Under similar conditions, Molenaar and Chiu (2017) explored the sequences of cognition of a sample of elementary school students that engaged in writing an essay about living in another country. In both of these studies, authors did not attempt to measure creativity, but rather group and individual processes to contribute with our understanding of how groups and individuals learn and create. Moreover, Johnson and D'Lauro (2018) focused on group ideas generated through brainstorming sessions to explore what types of ideas groups are more likely to select as the best idea. For this reason, they administered brainstorming rules (i.e., avoid criticism, produce many creative ideas, and combine and develop existing ideas) Osborn (1953) , and let participants write their ideas on how to improve freshmen's transition into college life on an e-chat room, along with their group members. Idea evaluation and selection was first based on what subjects considered a 'good idea', and later based on whether ideas were original and feasible (i.e., creativity characteristics).

Finally, because the literature on networks and innovations has explored the nature of social structures for innovation in the context of organizations, creativity and innovation are sometimes confounded on a single dimension, under the assumption that both required similar cognitive and contextual stimuli to emerge. For instance, research on networks has operationalized creativity in different forms of tangible innovations, like the number of patent registered (Fleming et al., 2007), or new standard procedures for engineering optimization (Leonardi and Bailey, 2017). In other cases, creativity is not directly operationalized within a defined set of variables, but instead, authors focused on the conditions that would facilitate individual and group creativity, like the costs associated with transferring knowledge across the network (Reagans and McEvilty, 2003), or finding the appropriate resources (Borgatti and Cross, 2003), or social benefits, like power and prestige (Burt, 2004; Burt and Merluzzi, 2016). Differently, the study of Dawson et al. (2011), contextualized on a school setting, used self-reported creativity as a measure individual creative capacity. Moreover, SNA entails different methodological approaches compared to standard statistics and qualitative methods, because must deal with relational data measured in the form of number and nature of social ties actors declare within a well defined network, normally formed by the workers in the organization, or students in a classroom.

In general, most of the SNA studies reviewed for this papers mirror quantitative studies in the sense that rely on statistical models. For instance, Fleming et al. (2007) used patent data, which facilitates tracking the social collaborative structure that gave life to the new combination of ideas and its later applications for new developments. For this reason, they focused their attention on U.S. utility patents granted between 1975 and 2002. The authors conceptualized new combinations or generative creativity as the appearance of pairs of previously uncombined ideas, in this case, patent categorizations, within a focal inventor's domain of patents. In addition, using new combinations is operationalized as the number of times a novel recombination is used by other inventors. To test their hypothesis on collaborative brokerage and the value of previous experience in team creativity, the authors included predictors like cohesion, the inventor's experience, the number of companies worked for, and external ties. Moreover, Reagans and McEvily (2003) hypothesized the effects of network cohesion and range on the costs of transferring knowledge (i.e., ease of knowledge transfer) in a RandD company. For testing their predictive model, the authors used a set of predictors like knowledge codifiability (i.e., 'degree to which information can be encoded'), common knowledge (i.e., social similarities, tenure and expertise), along with tie strength and network structure gathered from a combination of census (i.e., fixed roster of actors within the network) and egocentric (i.e., ego-generated list of ties) techniques. Later, Leonardi and Bailey (2017) used a multi-method approach to explore the conditions under which new engineering procedures (i.e., innovations) emerged and were use in offshore divisions from a large automotive firm. The research method included observations and interviews, and network data through a sociometric survey ('With whom have you worked on...'). The network metrics were used to predict network constraint, and defined as a summary of network features that reflect individuals access, or lack of thereof to structural holes. Analysis of interviews focused on identifying the structural interactions and engineering related processes that allow engineers to identify a potentially good idea, and the strategies used for them to diffuse it across the organization. It is worth noting, that even though observations and interviews are not different from standard procedures for data collection, the focus of analysis and coding are directed towards social interactions within a bounded network that is larger than the focal group.

2.3.5 Methodological Decisions for the Study of Creativity

Based on the different methods used to explore the variables and processes that foster group creativity, it is worth recognizing that each approach affords researchers with unique and interesting tools for understanding the complexity of subjects collaborating and developing ideas. From what we have learned, group creativity is a complex phenomenon that depends on individual attributes and motivations (Baer et al., 2008; Taggar, 2002; Sitar et al., 2016), group processes and particular dynamics or synchronies that would allow individuals to experience comfort for sharing and discussing with their teammates (Baruah and Paulus, 2008; De Dreu et al., 2011; Goh et al., 2013; Wise, 2014), all of these depending on the social structure where the group is embedded, and the nature of members' social ties (Burt, 2004; Borgatti and Cross, 2003; von Held, 2014). In simple terms, the likelihood of teams experiencing creativity and social learning is not a function of isolated factors, and the reason why research on group creativity includes multiple set of predictors. One important assumption that is present in the domain of groups and creativity, is that the collective performance will always include a creativity component at both individual and team-level, no matter the nature of activity. For obvious reasons, unscripted (i.e., unpredictible) tasks are better fit for triggering motivation and effort for creative thinking than well-defined and close-ended, yet in essence, both demand the existence and development of appropriate new knowledge (i.e., individual creativity). Further, analysis and ratings of groups' outcomes offer interesting evidence to explore subjects' knowledge, and creative dimensions, like relative originality and usefulness, which are ultimately expressions of groups' experiences and expectations (e.g., Thompson, 2003).

Moreover, SNA provides a comprehensive set of methodological tools that afford researchers the ability to aggregate variables collected in traditional forms, like survey instruments, and observations and interviews. Accordingly, beside mapping the pattern of social connections in the network, SNA allows the addition of individual attributes (e.g., gender, grades, group membership, etc.) into these social ties (e.g., Leonardi and Bailey, 2017), which would facilitate the understanding of how ideas and resources flow within and between subjects and groups that may share (or not) attributes. In addition, observations of collective performance, as well as interviews of participants would afford information that researchers are unable to collect through surveys. Individual or group strategies, attitudes and behaviors, etc., or interactions with technology or with actors outside the bounded network, are possible experiences that researcher may access through observations and interviews. Yet, as mentioned earlier, the network perspective for analyzing qualitative data differs from traditional approaches in the sense that the former perceives the social phenomenon as part of a social system, whereas the latter might explore it as isolated. In conclusion, and because group creativity and social learning are complex functions of the information and resources available within the social context, a network approach of group creativity is expected to provide deeper insights into creative dynamics.

2.3.6 Final Reflections for Physics Education Research

Now, in the context of an undergraduate physics course, understanding and exploring students' experiences from the lens of creativity and social learning, entails the notion that some dimensions of the learning process reflected in the course activities are creative practices that subjects must engaged in. A first individual component of this creative dimension lays on the conceptualization that knowledge development consists of new (i.e., original) logical associations between prior and physics content, that provide effective (i.e., appropriate) understandings of the physical world (e.g., semantic network) (Molenaar and Chiu, 2017). Second, the mentioned cognitive processes for constructing meaning are unlikely to happen in isolation, and therefore need a social system with resources that facilitate knowledge transfer for the generation of new and appropriate ideas. Interactions with the learning materials could work for some independent learners who might trust on their own abilities to build physics ideas (Sitar et al., 2016). Yet, one should presume that classrooms would have students with diverse levels of prior physics understandings, background experiences, as well as personal attributes and learning orientations, therefore, individual work might not be the right strategy for everyone. In this scenario, having a classroom with heterogeneous knowledge and experiences might provide social benefits, but only when students have opportunities to develop a social network that enables them the advantages of diverse resources (Borgatti and Cross, 2003), or cohesive clusters where students would engage in intense scrutiny of the content (Rhee and Leonardi, 2018). Consequently, group activities like solving problems in physics classrooms are preferred over individual tasks, as would give students these chances to work with more or less capable others, close to their zones of proximal developments (ZPD) (Vygotsky, 1978).

Consequently, classrooms are well-defined social systems that could mimic the conditions for knowledge transfer and creativity, known from the research literature in networks and innovations. An important consideration for creative recombination is the presence of diverse knowledge flowing through social ties, or sources of non-redundant knowledge (Burt, 2004). One may argue, however, that the latter condition is unlikely in a classroom setting because there is a physics curriculum and learning goals that are expected to be developed by every student in the class. Nonetheless, and in terms of knowledge transfer, the latter scenario assumes that every student is somehow able to form strong ties with the instructor and each other in a cohesive network, guiding to fair amounts of common knowledge and communication codes that would ease the transfer of complex physics ideas to the entire classroom (Fleming et al., 2007). Yet, it is fair to assume that in a regular classroom students are likely to show different levels of segregation and clustering, having students with either cohesive or sparse networks. This means that not every student would interact with each other through strong ties, nor with the instructor, and therefore restricting the flow of physics ideas to cohesive sections. Moreover, the relative strength of in-class social ties would control the speed and effectiveness of information flow, respecting the fact that complex knowledge is best learned through strong ties, whereas simple information flows easily through weak ties (Hansen, 1999).

Furthermore, whereas cohesive student networks would facilitate learning of physics ideas, weak ties that bridge structural holes (i.e., linked to nodes that are not connected to each other), would enable students to access non-redundant information (Granovetter, 1973). In this context, non-redundant information relates to physics content, and most likely would consist of students' physics conceptualizations, new strategies or applications of physics content for solving problems, or a combination of these that might be perceived as novel and might facilitate others' comprehension. Consequently, students who are surrounded by a cohesive network, but also connected to isolated groups in the periphery would have a great advantage over the rest (Reagans and McEvily, 2003). In addition, those peripheral groups or individuals could also get a social benefit from their ties with cohesive groups, as they may receive, for instance, simple evidence of performance standards in problems solving, or complex insights on physics conceptualizations, depending on the nature of their ties. These suggestions may depend strongly on whether students have social capabilities to communicate information in appropriate ways, as well as the disposition to share and asses it critically, otherwise this social engagement may have detrimental effects over performance, mainly due to ineffective interactions. These social conditions for creativity and innovation are not necessarily true in every physics course. Regular lecture-based instruction does not facilitate communication and network development, needed for knowledge transfer and building. In contrast, in active learning environments, participation is a key ingredient, yet these conditions do not end up facilitating social mobility for social capital. For this reasons, I propose certain instructional conditions that would model physics classrooms' networks for creativity and social learning, and whose effect can be tested through SNA.

First, social mobility for collaboration implies a change in the classroom culture, or a transition from an individualistic conceptualization of learnings and assessment. This cultural change might be possible through instructional innovations for collaboration and social learning, like collective accountability, assessment, and rewards, with special attention to the importance of novel and useful ideas. Instructors would play a fundamental role in facilitating this transition if they use a classroom narrative that highlights the importance of creativity and learning, and encourages collectivity for over the individual achievement or failure. The combination of physics and creativity in a daily basis may motivate people who normally would have associated creativity only with arts and music, to perceive how social mobility for creativity, or what we may labeled as creative competencies, might influence their academic performance. Second, learning problems should be designed as group activities, but more importantly, these must be challenging enough to trigger social interactions, knowledge transfer and creativity. In line with Sawyer and DeZutter (2009), we could use unpredictable or ill-defined physics problems as appropriate learning activities for collaboration and creative engagement. The difficulty of ill-defined problems rely on designing and deciding on the appropriate constraining conditions that guide the situation, from a scenario with multiple possible responses, to one with a unique correct solution (Rietman, 1964).

According to research on innovations, organizations enjoy and take advantage of multidisciplinary interactions, meaning that multiple projects are been addressed in parallel on different subjects, contributing to organizational memory (Hardagon, 2002). The nature of physics classrooms differ dramatically from that scenario, however, we may introduce a fair amount of diversity by appropriately designing physics problems that diverge in nature and context, but agree on the underlying physics content. Under these circumstances, each group would be responsible for solving a unique physic problem, which would define a fertile ground for social mobility and knowledge transfer, particularly if the classroom narrative encourages creative outcomes in a competitive way. We may assume here, that the cultural transition from individual performance to creative thinking through social interactions will demand some time. Consequently, we may observe different motivations for social interactions across groups throughout implementing a methodology of this nature. For instance, at the beginning of the course, having either unique or multiple problems being addressed by different groups may not make a difference in terms of knowledge transfer and tie formation, as students might not have developed yet a comprehensive understanding of the importance of social interactions, for learning and creativity. In this scenario, we may even observe higher social mobility with unique rather than multiple problems, because groups would have a common ground to discuss, while with multiple problems they may feel that they are on their own. This hypothetical lack of interactions outside groups could foster group cohesion, but at the expense of brokering. To tackle this problem, instructors could utilize formal moments of network oscillation during problem solving sessions (Burt and Merluzzi, 2016), where group members would assume the role of act as brokers, with the goal of finding good ideas in other teams. This simple practice is expected to afford multiple individual and collective benefits for central and peripheral groups. First, individual networks would develop cohesiveness within their respective teams, but also towards external ties, which might bridge structural holes in the classroom, facilitating transfer of diverse knowledge (Reagans and McEvily, 2003). Second, network oscillation might provide awareness of how resources are scattered across the classroom network, that is, who are the good students, the creative ones, the accessible and friendly peers, etc., which ultimately would ease information seeking and social learning (Borgatti and Cross, 2003).

A learning context like this would require first a physics curriculum that allows for the implementation of periodical problem solving sessions, and the design of unscripted or ill-defined problems. Second, the classroom must contemplate a reasonable number of students in order to evidence a hierarchical social system through which information and resources can flow. In addition, the physical space should allow students and groups to move around the classroom. Third, an instructor or group of instructors, willing to address creativity along with physics appropriateness, and assuming a secondary role during problem solving sessions. Accordingly, instructors must overcome the instinct of providing clear information to students' inquiries, but rather they should give directions and indicate which student or group in the class could know the answer. This last element of instructors' role might be the cornerstone for modelling physics classrooms for creativity and social learning, because if they keep assuming the responsibility of facilitating information, students and groups might never experience network development beyond strong ties with the instructor.

Chapter 3

Materials and Methods

Chapter 3 introduces a description of the methodological details followed during this research. First, I present a description of the Research Design, where I summarize the technical and contextual details surrounding the project, as well as goals, teaching and learning conditions, periods of study and variables for analysis. The second section (Research Questions and Goals) introduces the arguments for defining the research questions and goals that guided this study. Later, the section Research Setting and Subjects describes the nature of the physics course where this study was performed, research subjects and the engineer majors, and finally, the type of instruction and teaching strategy implemented by university instructors in each of the three sections where data was collected. I then introduce the different forms of data collected in this study, which includes the ill-structured problem students had to solve, physics grades, qualitative data, network measures and control variables. Finally, this chapter ends with a description of the analytical steps conducted to respond to each of the three research goals defined for the study.

3.1 Research Design

This work consists of a descriptive case study using qualitative and quantitative methodologies, conducted in three sections of introductory physics courses designed for engineering majors in a University in northern Chile. This research investigated problem solving, physics learning and creativity, and the effect of students' social networks when they solved well and ill-structured physics problems. For this purpose, in collaboration with course instructors, we designed a battery of ill-structured problems grounded on real-life situations that could be administered each week during problem solving sections. How often they actually were administered differed by section. One section (Traditional section) used the ill-structured problems only once – during the week of data collection (7th week of the semester). This section used more traditional well-structured math-based problems during all other problem solving sessions. In the second section (Mixed section), the instructors implemented ill-structured problems every other week alternating with well-structured activities. In the third section (Treatment section), the instructors implemented ill-structured problems every week. I hypothesized that these different approaches to instructions (more details at description of Research Setting & Context) would affect the ways in which students collaborated, the physics ideas and concepts they articulated, and the social structure of the class, which would enable performance through different social mechanisms.

At the end of the semester, the students in all three sections faced the same tasks during the day of data collection (i.e., ill-structured problem), as well as a physics test designed that included well-structured problems. To explore for learning opportunities, as well as differences/similarities across sections and student groups, I collected and analyzed data from audio recordings of groups' discussions during problem-solving of ill-structured activities, performance on both type of learning activities (i.e., solutions to ill-structured problem and grades on physics test) and different social networks. Additionally, the university provided socio-demographic variables, as well as past performance on standardized tests for control variables.

3.2 Research Questions and Objectives

One of the primary goals of this study was to explore whether ill-structured problems enable creativity, (defined here as the novel and appropriate use of physics ideas). If so, such problems could be a powerful instrument for students to not only engage in knowledge building through the transfer of physics ideas, but also a tool to assess students' ways of using concepts and ideas into their solutions. In contrast, the constrained nature of close-ended (i.e., well-structured) math-based physics problems may limit the number of topics students address, because of the limited elements embedded in the design of the problem. These elements normally consist of physics principles and their mathematical representations; therefore, one would not expect group discussions that go beyond the use of the mentioned math-oriented issues for solving well-structured problems, as the literature has shown (Byun and Lee, 2014; Kim and Pak, 2002). In contrast, unconstrained (ill-structured) problems require students to make assumptions, opening the scenario to the emergence of additional topics for discussion, which may push participants to address qualitative physical descriptions attempting for apply additional physics concepts into make their subjective assumptions. Therefore, it is expected that ill-structured problems would provide a richer context for the emergence of creative ideas, in terms of learning opportunities (i.e., mini-c creativity) and good ideas for solving problems (little-c creativity) (Kaufman and Beghetto, 2009). In other words, ill-structured problems would enable the development of Amabile's (1996) knowledge and creative-relevant skills , here represented in learning physics content, and the use of this new knowledge for idea-generation (e.g., assumption making), respectively. Both of which are fostered through collaboration and group discussion (Sawyer, 2003). Based on the latter description of learning possibilities that may emerge from ill-structured problems, research question 1 asked:

RQ1: What are the various ideas and processes engaged by groups when solving an ill-defined problems?

Because solutions to ill-structured problem may constitute interesting opportunities for assessing the degree to which students are comfortable applying a variety of physics concepts to real-life scenarios, and therefore paying attention to solutions' characteristics may reveal important insights about students' conceptual understanding, and familiarity with physics content, as well as other non-physics ideas that are needed for creating solutions. Further, the fact that each section utilized a different combination of problems, as well as strategies to guide the problem solving session (more details on this on Research Context and Subjects), it is likely that solutions would reflect each section's way of utilizing concepts and non-physics ideas from the respective section. For this, research question 2 asked:

RQ2: What are the set of physics concepts and characteristics utilized in students' solutions to ill-structured problem from each section?

Finally, and based on the literature presented in the previous chapter regarding well- and ill-structured problems, performance features and conditions for solutions on both types of activities, the final goal of this study is to determine whether different social structures afford success on well and ill-structured problems. As it has been described, well-structured problems consist of closed-ended and frequently math-based problems that can be superficially solved by identifying the right set of physics' equations and rarely the need of knowing the appropriate concepts (i.e., 'plug and chug' strategy) Byun and Lee (2014); Kim and Pak (2002). These elements and resources are easy to access in the context of a class (e.g., notebooks and books, lecture materials, etc.). For this reason, one may expect these problems would not demand intense social interactions for pursuing useful resources for finding the correct unique answer. However, in the case that students experienced the need to seek out information, the question lays on whether this social engagement is invariant to all types of students, or depends on one's status? Here, one may think that students with little physics knowledge may be more prone to reach others for the right information in order to solve their academic needs in the face of well-structured problems, whereas students who are more familiar with the content may not experience such need because they may already have a sense of how to utilize the physics information in service of the problem at hand.

In contrast, ill-structured problems tend to be complex situations that require decision-making and creativity to determine how to use and implement physics ideas, by generating assumptions that would constrain the open-ended scenario into a well-structured one (Fortus, 2008). This process demands a different set of ideas, understandings and strategies that students may already possess, or could access within the social system of the classroom. Therefore, groups and individual network might have a different effect over groups' solutions. Based on this, research question 3 asked:

RQ3: What are the network structures and measures (e.g., cohesion and centrality) that will predict good performance on well-structured problems and ill-structured problems in physics?

Further, because each section engaged in different combinations of problems, as well as instructional strategies to present the content and guide problem solving sessions, these variable may have influenced the social system of the class, and therefore academic success on well and ill-structured problems may respond to different structures. Accordingly, research question 4 asked:

RQ4: Do different sections enable academic success in well and ill-structured

problems through different social structures?

3.3 Research Setting and Subjects

The research settings consisted of three undergraduate physics courses in a University in Northern Chile. The study was conducted in one course at NCU during two months of the academic semester August-December 2018. The course content consisted of Newtonian Mechanics, which addressed content such as Vector Algebra, Kinematics, Newton's Laws, Conservation of Mechanical Energy, Linear Momentum, and Universal Law of Gravitation. The course dedicated 3.0 hours each week to lecture-based instruction, 1.5 hours per week to lab practices, and 1.5 hours per week to problem solving sessions. As prerequisite for this physics courses, enrolled students must have passed algebra, and univariate differential and integral calculus.

Research subjects were engineering majors in their first or second year of college education, pursuing a careers on either Industrial Civil Engineer or Software Civil Engineer. A total of 113 students were enrolled in the course, divided in three sections (Traditional = 37; Mixed = 39; Treatment = 37). Of this total, only 67 decided to respond the survey instruments (Traditional = 32; Mixed = 19; Treatment = 16). Students decided the section in which they would like to go when enrolling on the course; yet, this decision was made without any information regarding the name of the instructor.

Finally, each section utilized a different set of physics problems. Traditional sections used well-structured and math-based problems during the semester until the day of data collection, where the same ill-structured activity was administered. Mixed section alternated with well and ill-structured problems every other week, while Treatment group used only ill-structured problems. Importantly, each instructor engaged in two alternative strategies when guiding the session where these problems were administered.

Instructors of section 1 (Traditional) and 2 (Mixed) responded to students' inquiries and questions by providing the information requested, whereas instructor of section 3 (Treatment) responded to these inquiries by encouraging social interactions; that is, the instructor guided students' attention to other members in the classroom who may have had the answer. The constant use of ill-structured problems in Treatment section was accompanied by the instructor highlighting the importance of assumptions and creativity for solving the open-ended activities.

3.4 Data Collection and Analysis

To respond to RQ1 (What are the different ideas and processes engaged by groups when solving and ill-defined problems?), I gathered audio on 4 student groups during the problem solving session (1.5. hours) during the 7th week of the semester, while they solved an ill-structured problem (Fig 3.1), which consisted of designing a physics problems for high school students to elicit their learning on rotational motion. A total of 295 minutes of audio were transcribed using an online free tool (otranscribe.com), and by identifying first turns of speech engaged by different group members (e.g., *Student 1*: How did you obtain the number of revolutions? Did you multiply the number by something?; *Student 2*: There is one revolution and two revolutions). Later, I revisited the data to separate these turns of speech by message units (*Student 1*: ["How did you obtain the number of revolutions?] [Did you multiply the number by something?]; *Student 2*: [There is one revolution and two revolutions]), as the former may include more than one message unit, and consequently, a variety of ideas may be expressed during the same turn of speech.

The coding process was conducted in NVivo 12 plus, and was intended to elicit the different set of ideas and processes students groups engaged on for generating a physics

Task for Data Collection

To solve the following problem assigned to your group, consider the following strategies:

- Describe the problem in terms of physics concepts and principles.
- Plan and define a strategy to develop a solution.
- Execute the plan and strategies to build your solution.
- Check and assess your results and appropriateness of your solution.

Problem:
As part of community activities at the university, you and your team have been selected to teach the kinematics of circular motion to high school students. It is known that individuals are capable of understand new content and information when this is contextualized, that is, applied and connected to daily situations, in order for the new information to be learned in a familiar context. Physics and math teachers from the school where your team will teach the physics of circular motion have been preparing their students in the needed mathematical content to ease their physics learning. With this, your team is responsible for identifying daily situations that would enable the study of circular motion, and create a couple of math-based problems for high-school students to solve.

Figure 3.1: Ill-structured problem designed for the day of data collection.

problem using the concepts and principles of circular motion. First, I reviewed 25% of the data, and identified emergent issues and ideas students discussed for solving the problem by attending to the dimensions that require decision making, and strategies for solving physics problems (i.e., algebra, conceptual understanding). This first analysis led to a first draft of coding definitions for themes. I met with and trained graduate students in qualitative research whose first language is Spanish (research subjects are Spanish native speakers) to review and re-define the codebook for the analysis of the data, with examples taken from the 25% of data utilized initially, until agreement was reached. Later, together we coded 15 (6.25%) minutes of the transcribed data while negotiating the selection of codes. Finally, the trained graduate students coded independently 45 min (18.25%) of the data, obtaining a Cohen's Kappa of 0.94 for inter-rater reliability.

The analysis yielded to the identification of two main categories of themes engaged in by groups during the generation of a physics problem. Table 4.1 shows these categories (Decision Making and Problem Solving Strategies), and the different themes corresponding to each category. This analysis and its result enable a response to RS1,

Table 3.1: Codebook of emergent categories and themes addressed by 4 student groups during the task of generating a physics problem.

Code	Description
Decision Making	
Learning Goals	Team discussed and makes decisions regarding the learning goals for the generated problem, and expectation on what the targeted students should learn from it, which mediates the degree of difficulty taking in consideration the school level of the targeted students.
Physics Concepts and Procedures	Team identifies, poses and decides on the physics concepts to use into the problem, as well as the ways in which these concepts aligned with the generated problem to be well-structured, and consistent with the task requirements.
Problem Context and Wording	Team pose and decides on the contextualization of the problem (i.e., place, subjects, actions etc.), and the wording of the problem.
Discussing Magnitudes and Units	Team discusses and decides the magnitudes scores and values, as well as measurement units for the physics concepts (e.g., 10 km/h, 20 s, 2.5 km) to be introduced into the problem's description.
Prob. Solving Strategies	
Algebraic Procedures	Team describes algebraic steps to obtain physical quantities as a way of solving the problem, normally mentioned to justify the appropriateness of the designed problem.
Physics of Circular Motion in Context	Team engages on a qualitative description of the physics regarding the circular motion in the context under consideration for the problem.

as I obtained evidence of the different set of ideas addressed by student group for the creation of a learning activity, as well as nature of processes that facilitate solving the problem.

To respond to RQ2 (What are the set of physics concepts and characteristics utilized in students' solutions to ill-structured problem from each section?), I gathered students' solutions to the ill-structured problem presented in Figure 3.1. A total of 26 problems

(Traditional = 10; Mixed = 9; Treatment = 7) rotational motion were collected. In order to conduct the analysis, I translated these problems from Spanish to English, which were revised by a native English speaker knowledgeable in physics. The analysis of these solutions (i.e., physics problems) was conducted on NVivo 12 plus. This qualitative description comes from the identification problems' attributes and characteristics, such as physics concepts used as data and/or questions, type of information, contextual details among others. In addition to the emergent codes, I analyzed student problems' based on their cognitive demand on processes related to retrieval of information, comprehension, analysis and knowledge utilization, as defined in a taxonomy of introductory physics problems (Teodorescu et al., 2013). I conducted a first wave of coding which led to an initial version of the codebook, who was revisited in collaboration with a trained graduate student in qualitative analysis and physics content. After agreement, an independent wave of coding was performed, where both covered 40% of the data (10 problems), obtaining a Cohen's Kappa of 0.9 for inter-rater reliability.

3.4.1 Social Network Analysis

To address RQ3 & RQ4 (What are the network structures and measures (e.g., cohesion and centrality) that will predict good performance on well-structured problems and ill-structured problems in physics?; and Do different sections enable academic success in well and ill-structured problems through different social structures?), I collected data on students' social networks, academic performance on well and ill-structured problems, as well as socio-demographic variables to use as control for quantitative analysis.

Performance variables (i.e., physics grades and problem elaboration) came from physics scores to a test designed by instructors over three well-structured physics problems. Physics grades were shared by the instructors three weeks after the day of data

Table 3.2: Code description of problem characteristics.

Code	Description
Physics Concepts Asked	Physics concepts used as problem items (e.g., angular speed, tangential acceleration).
Type of Information	
Ready-to-Use Info	Data is explicitly presented in the problem and with appropriate units for its use.
Conversion of Units	Physical quantities that need conversion to respect the IS of units (i.e., m and s).
Text to Math	Physics information is presented in written form and needs translation into mathematical expressions (e.g., "begin its motion from rest" or "uniform motion").
Algebra Transformation	Physics information for solving the problem needs algebraic steps for accessing and using it.
Information Research	The problem requires researching appropriate magnitudes to solve the problem.
Assumptions	Problem forces students to assume particular characteristics of the problem, such as constant acceleration, or the position of the 'particle' that describes the circular motion.
No. Phys. Concepts Asked	Number of physics concepts used as problem items.
No. Equations Needed	Number of equations required to solve the problem.
Contextual Details	Elements from real-life activities, and/or actors witnessing or engaging in actions.
Word Count	Number of words used on the problems' description.
Cognitive Demand	Taken from a taxonomy of introductory physics problems (Teodorescu et al., 2013).

collection, without the possibility to review the assessment instrument, nor students' solutions to these problems. Further, problem elaboration is a variable constructed from the sum of standardized problem characteristics detailed in Table 3.2. This variable aimed to measure the degree of elaboration and complexity of the problem designed by students.

In order to identify the social structures that enable good performance on both well and ill-structured problems, I designed a network survey administered online through Qualtrics. This network survey was administered to three sections at the end of the problem solving session on week 7 of the academic semester. The survey consisted on two questions:

1. Information Seeking: From whom had you sought information for solving the physics problem addressed this session?;

2. Good Students: Who is a good physics problem solver in your class? (i.e., a student you believe is good at understanding physics content and solving physics problems)

To facilitate students' responses on each of these questions, I included the roster of students enrolled in each section. For this reason I shared three different surveys, each containing the latter questions but with their respective section student roster. Consequently, subjects responded by selecting the individuals in their sections from whom they sought information, and the ones that are perceived as a good students. Both questions led to directed (i.e., ties are not necessarily reciprocal) and binary networks (i.e., links between nodes either exist (1) or do not exist (0)). The network of information seeking is designed to reveal whether students engaged on social interactions for the sake of finding resources and ideas for solving the physics ill-structured problem. Borgatti et al. (2013) suggest that because flow ties are difficult to obtain, 'seeking information' ties can be perceived as proxies of information flow. Using good student network is thought to enable an additional dimension to reveal what type of students engaged on information seeking, to then explore whether this perceived prestige is a valuable contributor to the social processes that affect academic success.

The network variables used for this analysis were computed from the network of information seeking (i.e., response to survey question a), using UCINET 6 for Windows (Borgatti et al., 2002). The first set of structural variables computed consisted on different metrics of network centrality, such as degree, indegree and outdegree centrality.

Later I obtained measures of network density, constraint and structural holes, to then determine different variables associated with brokerage (Borgatti et al., 2002), defined as bridging connections between unconnected groups within the network. Following I show the list of variables used for network analysis.

List of dependent, independent and control variables used for social network analysis:

1. Dependent Variables
   (a) Physics Grades: Scores of physics test designed by instructors, containing three well-structured problems. Administered at the 8th week of the semester.
   (b) Problem Elaboration: variable created as the sum of the scores on problem's characteristics shown in Table 3.2. It is a performance variable generated to determine the relative degree of elaboration and complexity of the problem.
2. Network Predictors
   (a) Indegree: Network measure of centrality that counts the number of incoming edges or social ties for a given node, that is, the number of links directed from other individuals within the network towards a focal actor.
   (b) Outdegree: Network measure of centrality that counts the number of outgoing edges or social ties for a given node, that is, the number of links directed from the focal actor towards other individuals within the network.
   (c) Degree: Network measure of centrality that counts the number of edges (i.e., social ties) connecting the focal actor.
   (d) Betweenness: Network measure of centrality that counts the number of times a focal actor is located in the shortest path (i.e., geodesic distance) between two other nodes in the network. Computing this measure requires

first, to count for the total number of paths that can connect nodes i with q, and then determine the number of these shortest paths where the focal node j falls in between. The mathematical representation of betweenness is: $b_j = \sum_{i<q} g_{ijq}/g_{iq}$, where g_{ijq} corresponds to the shortest paths linking i and q through j, whereas g_{iq} is the total number of ways of connecting i and q without the restriction of passing through j. Here, students with zero betweenness centrality can be either isolated or central members in a dense network where every subject is connected to each other.

(e) Eigenvector: Network measure of centrality of social influence within a system, as it depends on whether the nodes tied to the focal subject show high or low degree centrality themselves. Accounting for the connectivity of one's friends is key for flow processes (Borgatti et al., 2013), to the extent that friends with social relationships outside one's social domain might boost chances of receiving and sharing valuable information for learning, innovation and social status. The algebraic representation of eigenvector is as follows: $e_i = \lambda \sum_j x_{ij} e_j$. Here, e_i is the eigenvector centrality of node i, and the largest eigenvalue of e_i. Moreover, x_{ij} can take values of 1 or 0 depending on whether nodes i connected to j or not respectively. That is, eigenvector centrality of node i is proportional to the sum of its neighbors' eigenvector centralities.

(f) Density: Network measure of cohesion consisting on the percentage of edges connecting a given actor relative to the total number of ties in the case that all nodes in the network were connected. An isolated node will show a density of zero due to the absence of ties with the others, whereas a density of 1 will indicate that the focal node shows ties with every other alter within the network. According to the literature on social networks, density provides some context to degree centrality, and enables interpretations such as social investment and embeddedness in the system, as relative to the overall connectivity.

(g) Constraint: Network measure that accounts the number of redundant social ties, that is, the degree to which a node spans ties with others who are also connected to each other (Burt, 1992). Constraint is an inverse measure of brokerage, or the node that bridges isolated portions of the network, thus accessing structural holes. High constraint will indicate that a node is totally invested in a group of already connected others, and will therefore have access to zero structural holes. The definition introduced by Burt (2004): $C_i{=}\sum_j c_{ij}$ $,i{\neq}j$; $c_{ij}{=}(p_{ij} + \sum_q p_{iq}p_{jq})^2{,}q{\neq}i{,}j$, where C_i is the constrain of node i, and c_{ij} an index that indicates i's investment on its relationship with j, counting direct (p_{ij}: proportion of tie strength between i and j, relative al all of i's ties) and indirect ($\sum_q p_{iq}p_{jq}$): proportion of tie strength through indirect paths connecting i and j via q.)

(h) Structural Holes: Network measure that accounts the number of times a node is the unique connection between two otherwise unconnected sections of the network Burt (2004, 2005), thus accessing to new ideas.

(i) Coordinator: Brokerage measure that counts for the number of times node i bridged connections between j and q, being i, j and q members of the same group.

(j) Gatekeeper: Brokerage measure that counts the number of times node i bridged connections between j and q, being the source node j a member of a different group than i and q, which are in turn members of the same group.

(k) Representative: Brokerage measure that counts the number of times node i bridged connections between j and q, being the nodes i and j members of the same group, while the destination node q belongs to a different group.

(l) Liaison: Brokerage measure that counts the number of times node i bridged connections between j and q, being all three nodes members of a different group.

3. Control Variables

(a) UST: National (Chile) standardized test for higher education application. The score used here correspond to the average between Language and Mathematics test scores.

(b) Section: Categorical variable indicating membership to sections Traditional (1), Mixed (2) or Treatment (3).

(c) Engineer Major: Categorical variable indicating enrollment on Industrial Civil Engineering (1) or Software Civil Engineering (2).

(d) Female: Categorical variable indicating whether participants are male (1) or female (2).

(e) Good Student: Indegree centrality on the network of good students, and accounts for the number of times a student in the section is perceived by other as a good physics student.

(f) Type of High School: Categorical variable that indicated the type of high school students graduated. Public (1), Private (2) or Charter School (3).

(g) Same City: Categorical variable that indicates whether subjects graduated from high school at the same city where the University is (1) or a different one (0).

For a graphical representation of these different brokerage measures, Figure 3.2 shows a network with eight nodes who belong to three different groups (green, blue and orange). According to the figure, the lack of social ties between nodes C and D, or between groups green and blue indicates the presence of a structural hole in the network. Node F bridge connections with both groups (C and D), and therefore has potential access to novel information from both groups, as well as control over the flow of knowledge towards both groups. This type of brokerage is defined as liaison, as the node broke ties with members from two different groups. When brokerage occurs with members from the same group who are not connected, like node C (connected to A and B, yet these do not display a tie), this broker role is called coordinator. A gatekeeper broker is a node that span non-redundant ties with nodes outside its own group, has connections with its own group members, and engages in bringing information from the outside node, while the destination of that information is a node within its own group. On Figure 2, nodes C, D and F display such type of brokerage as these display ties with nodes outside their own units (sources), but at the same time engaged with teammates, and therefore, may have access to novel information from these outside sources and bring it to the group. Finally, representative brokerage differs with gatekeeper in the directionality of the information flow, as it is defined as brokering knowledge between nodes from the same focal group and a different group, but with information flowing from the group to outside. Again, nodes C, D and F may have engaged in this type of brokerage, as they may have access information from others within their own groups, and then shared it with their outside sources.

Finally, the University where this study was conducted allowed access to records on different set of variables used as control. Among these confounding variables, I used scores on University Selection Test (UST), a national standardized test that every student must take after finishing high school in order to be eligible for accessing higher

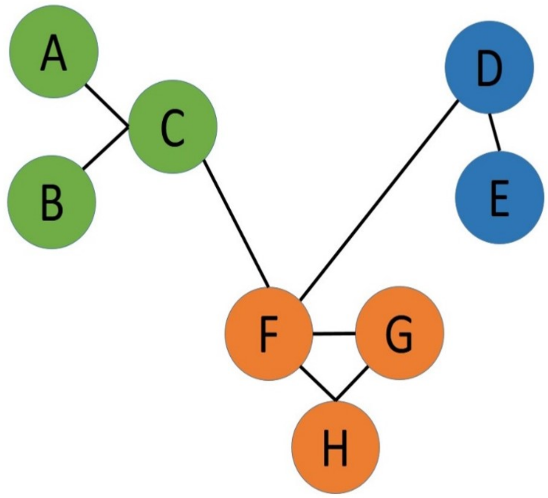

Figure 3.2: Network diagram with eight nodes corresponding to three groups.

education. I also controlled for course sections, students' gender, engineer major or not, type of high school students graduated from, and whether they graduated from a high school located at the same or a different city as the university. Finally, from the network of good students I used students' indegree centrality as a measure of perceived status and prestige in the context of physics.

Analysis of Networks and Performance

After removing missing cases, the number of students remaining for analysis was N = 67. In order to respond to research questions 3 and 4, I used ordinary least square multiple regressions (OLS) on the continuous dependent variables (i.e., physics grades and problem elaboration) to explore the predictive power of network structures, as well differences in performance by sections.

The first step of analysis consisted of testing the existence of differences across the three sections on the network metrics used as predictors of success in the analysis through regressions models. These models were fitted to using control variables along with the respective sections as categorical variables, with the network measures as dependent variables. Exploring network differences across sections enabled a better understanding on the social processes students engaged when seeking out information, and to whom (i.e., good students, same engineer major, city or high school), which ultimately facilitate the interpretation of further performance differences in well and ill-structured problems.

Later, a similar analysis was made to predict grades and scores on problem elaboration, but here using network attributes as independent variables. The predictive models for grades and problem elaboration include interaction terms between sections and the key predictor (i.e., network variables), which enable a comparison and interpretation on whether the network variable has a similar effect over the whole sample, or its effect over students' outcomes depends on the learning environment defined by the type of problems and teaching strategy. In order to ease interpretation of regression coefficients, all predictors were standardized. For interpreting the regression coefficients of categorical variables such as sections, school type and engineer major, readers must consider that the coefficient emerges as the difference between the variable in the model and the baseline categories, section 1 and public schools respectively.

Chapter 4

Results

4.1 Groups Processes and Discussion

In this results section, I explore the different categories and themes that were identified from the data and how the four groups of students addressed these. These categories and themes (see Table 4.1, in Chapter 3) respond to the different set of ideas, arguments and processes groups engaged during the activity that enabled them making decisions and the transfer of physics content into real-life scenarios. Here, first I describe the nature of these categories and themes, utilizing direct examples taken from the data. For doing this, I investigated four student groups, two from each Traditional and Treatment section, which were pointed out by their respective instructors as groups with good students. Further, I explore the differences across these four groups in regards to the observed frequency in which themes were engaged by them.

To respect the labels and sections that are used in the next result section, the groups that were analyzed in this section correspond to groups 4 and 8 from Traditional sections, and 6 and 7 from Treatment section. One task posed to the participants was to create a problem using the concepts studied in their physics course. In order to ground the evidence shown here to groups' outcomes, Figure 3 shows the problems generated by each of group.

Group 4- Traditional Section
Two friends bike together from school to the beach, a trip that takes 10 min. The perimeter of the bicycle wheel is 6 m, and the time that takes the wheel to complete a revolution is 3 s. Determine the distance covered by both friends knowing that they move with constant speed.

Group 8- Traditional Section
Donkey Kong wants to throw barrels to King K Rool. For this throws one with an angular speed of 2π rad/s. By knowing that at 3 s its speed is 10π rad/s, and that the barrel impacts at 5 s, determine: a. the angle covered by the barrel; b. the magnitude of the centripetal and tangential acceleration at the moment of impact at 6 cm from its center; c. frequency and period.

Group 6- Treatment Section
A person on his/her car wants to move from university campus to city downtown, a trajectory of 2 km in longitude. The car starts from rest with a constant acceleration of 10 m/s^2. If the car wheel has a radius of 30 cm: a) What is the wheel's final tangential velocity? b) What is the wheel's final angular velocity? c) What is the final angular distance? d) Determine the number of complete revolutions made by the wheel.

Group 7- Treatment Section
A group of college students had the brilliant idea to put one of their peers into a 1 m radius barrel, and decide to push. With such enthusiasm, students were capable of making the barrel spin with an angular acceleration of 2 rad/s^2. If the initial angular speed was 2 rad/s, respond: a) If the student inside the barrel reaches more than 150 complete revolution in the first 30 s, he/she will vomit, would this happen?; b) Determine the angular and tangential speed at 30 s.

Figure 4.1: Problems generated by groups 4 and 8 from Traditional section, and groups 6 and 7 from Treatment section.

I analyzed the student talk during the problem development to identify the topics addressed. Table 4.1 summarizes the observed frequency of themes by the categories, Decision Making (75.6%) and Problem Solving Strategies (24.4%), among the four student groups analyzed. The first category (Decision Making) refers to processes related to making decisions and generating ideas for the purpose of generating the problem. During these processes, teams discussed and decided on issues such as the learning goals of the activity, the concepts and procedures, the contextual details how these elements would be presented in written form. They also decided on the data to be included to make the problem well-defined and the questions that would be appropriate to ask taking in consideration the decided data. Based on the frequency shown in Table 4, one may say that decision making did demand most of the time when groups needed to create a physics problem, compared to other processes. Next, I identified a category of themes related to processes related to solving the problem, where students would verbalized the need of particular set of equations and concepts in mathematical form, along with algebraic procedures. An interesting theme of discussion emerged here in the form of qualitative description of the physics surrounding the phenomena being discussed for the problem.

Table 4.1: Frequencies and percentage of categories and themes addressed by 4 student groups during the task of generating a physics problem for high school students.

Categories and Themes	Frequency (%)
Decision Making	
Learning Goals	25 (4.18%)
Physics Concepts & Procedures	209 (34.95%)
Problem Context & Wording	128 (21.4%)
Discussing Magnitudes and Units	90 (15.05%)
Problem Solving Strategies	
Algebraic Procedures	98 (16.39%)
Physics of Circular motion in Context	48 (8.03%)
Total	598 (100%)

4.1.1 Decision Making

To facilitate the understanding of the themes under decision making, it may help to remember the nature of the activity presented on Figure 1, where students were tasked with the challenge of generating a physics problem using concepts and principles of circular motion for high school students. This study hypothesized that engaging in such an activity would elicit students' physics understandings as well as encourage cognitive processes that are normally enacted by experts (i.e., teachers and instructors), such as assumption generation and familiarity in the face of uncertainty (i.e., uncertainty due to the open-ended nature of the problem). One may argue that the themes that emerged in this category mirrored the type of elements teachers and instructors decided on when generating their own learning activities, such as the learning goals, content and processes embedded on the activity to encourage thinking and knowledge building, and the pieces of information that make the task appealing (i.e., context) and well-structured (i.e., data). Next, I describe the nature and details of the ideas groups decided on for accomplishing this creative task.

Learning Goals

Here, student groups discussed and made decisions regarding the learning goals for the generated problem, and expectation on what the targeted students should learn from it, which mediates the degree of difficulty taking in consideration the school level of the targeted students. The general goal suggested by all four groups referred to their problems allowing secondary school students to exercise their physics knowledge (e.g., "The idea is that they would exercise with the problem we give them"). Because the ill-structured activity was framed in such a way that the outcome would help others to achieve a goal, it is not surprising that college students would negotiate this by taking into consideration both age and educational level of the students who would complete the problem, and the requirements of the task as an strategy to mediate the complexity of the generated problems. Consequently, secondary students' school level emerged in multiple opportunities as arguments in favor (e.g., "If we think on the students' age, they should know how to do such operations.") or against (e.g., "Maybe that is too much for a kid in 10th grade. Because that is something they would do in 11th grade."), the difficulty of the problem in terms of mathematics representations and concepts.

A portion of the discussion of the learning goals in Group 6 (Treatment) for instance, was concentrated on the reasons for using learning circular motion as the target concept, and its importance for them (university students) and the targeted secondary students. On this example, it is possible to perceive the intention of making sense of the activity and the overall objective of learning concepts and principles of circular motion:

> Student A: "What is the goal of this (activity)? I mean, of teaching this?"
> Student B: "What thing?"
>
> Student A: "All this equations and concepts."
>
> Student B: "For us or for students who would be solving this?"
>
> Student A: "Well, for both."
>
> Student B: "It is assumed that almost every movement is circular, as there is rare to find truly straight movements. These do not exist. You will see that this (movement) has no angles, but in reality it has."
>
> Student A: "It would be like explaining them (high school students) how these (movements) work."

Here the discussion about the learning goal emerged from the explicit goal of the task, yet not necessarily supported by the argument made by student B in regards to the ever-present circular motion, which attempts to highlights its importance by transferring and extending the real nature of motion upon a combination of circular displacements. The latter argument is interesting as students explicitly attempted to make sense of the content to be learned. This argument received no follow up but other team members.

Group 7 (Treatment) linked the goal of the task to what science teachers would do in the face of a similar task. The following segment shows this brief moment of reflection, where the group attempted to convey the appropriateness of their problem in coherence with the learning objectives:

> Student C: “We have to be clear with the goal, which consists of teaching and learning kinematics of circular motion to 12th grade students. So, it is like a teacher preparing to teach circular motion. That way, each element of circular motion we could link it to different contexts from daily life, or just one. It has to be didactic for them (high school students) to understand.”
>
> Student D: “Let us do problems similar to the ones our instructor has used.”
>
> Student C: “That is it, didactic.”

This segment is interesting as it provides evidence that, in finding the goal, students might think and reflect upon what experts [secondary school teachers] would do in contextualizing the content, and projected their own expectations into what a learning problem should look like. The effects of assuming experts’ roles goes beyond the focus of this study, however, one may presume that this thinking process would likely boost motivation in the face of the task, and more importantly, an approximation to the use of technical language. Finally, in Group 4 (Traditional), I observed a deeper reflection of the learning goals in which a student highlighted the importance of the real-life context for learning:

> “So, if you include a difficult exercise, but they do not know how to solve it through equations, they would remember that they tackle a problem involving a laundry machine where there was a circular motion and were able of calculating the speed. Consequently, and lastly, they would understand and know how to calculate angular and tangential speed for a laundry machine, and they would imagine the same type of motion but on different problems.”

According to this quote, the context would mediate the difficulty of the problem in the case that the targeted students were incapable of using the needed equations, as they would ultimately associate the context of the laundry machine with circular motion. Through this link, the students argued that learners would draw similarities in the use of equations for the purpose of calculating quantities across different scenarios. This, in essence, is the notion of transferring knowledge, that is, the use of information from a well-known to an unknown situation, and may be evidence of deep learning.

Physics Concepts and Procedures

During this process, the teams identified, posed and decided on the physics concepts to use in the problem, as well as the ways in which these concepts aligned for the generated problem to be well-structured, and consistent with task requirements. Defining procedures was clearly in direct connection with the learning goal, as teams engaged in the former process to meet the expectations previously defined. When addressing this theme, groups attended to and emphasized different set of elements, such as the algebraic steps through manipulation of equations, concepts and the combination of quantities for an appropriate problem structure. Section 2 of results dissects the physics embedded in these problems and how students decided to combined concepts. However, a brief read of the problems in Figure 3 would allow readers to identify the set of concepts used by each group. For instance, Group 4 (Traditional) and Group 6 (Treatment) selected linear concepts (speed, distance, acceleration) as initial conditions that would allow solvers to determine the number of revolutions completed at the end of motion, or the final distance covered or speed, among other questions. Similarly, Groups 8 (Traditional) and 7 (Treatment) decided to use the angular version of the latter concepts to determine the magnitudes defined as questions.

I observed two different sets of strategies for addressing the early stages of this process and making decisions: Equation-driven and Concept-driven. The first approach (Equation-driven) was observed in teams that primarily focused on the mathematical dimension of the problem for decision making, whereas concept-driven strategies emphasized the conceptual dimension of the situation to then reflect on mathematical representations. Group 6 (Treatment) was the one that mostly utilized an equation driven approach when defining concepts and procedures. For this purpose they suggested including the equations in the problem so that students could easily 'plug and chug' and find the solution (e.g., "I supposed we need to include the equations. That way they only need to replace."). Consequently, this process was guided by the (implicit) idea that a problem is constructed in the same way that one may solve it, which refers to following very structured set of steps, where equations and physical quantities play an important role (e.g., "So the problem must be in order. First you calculate one (value), which then allow you to find other."). The example illustrates the algorithmic nature of the problem developed by students from Group 6 (Treatment). Similarly, Group 8 (Traditional) engaged in such strategy for defining concepts and procedures, yet transitioned towards more qualitative descriptions of the phenomena after establishing the situation to be used. Evidence of a more qualitative approach is shown in the following suggestion made by one of the students:

> "It will start from rest, and that way we could calculate the movement of the barrel. So then, we would tell them that the barrel is accelerating constantly and that needs certain time in seconds to hit the target. Because after some seconds the barrel will be there, at its final position. That is, it will necessarily impact the target, so then they could begin their calculations for different things, like angle and everything."

This quote shows a brief and simple physics analysis of the situation used (i.e., a barrel is thrown to a person in a video-game setting), as the student analyzed the position and evolution of the object as long as time evolves, and enable further understanding of the procedures students are expected to go through for solving the problem generated by Group 8 (Traditional).

Even though deciding on concepts and procedures from the concepts is not absent from the attention to equations for decision making, the subtle difference is that these emerged after deciding on the concepts first. For instance, a student in Group 7 (Treatment) stated: "So let's create a situation where we combine angular speed, acceleration and all that. A situation that involves circular distance." This different approach enabled groups to create problems based on the relationship between concepts rather than on the exclusive use of equations. In Group 4 (Traditional), this was insinuated by a member arguing against the equation-driven approach in the description of the physics regarding the situation selected:

> "More than the equations, it would be to say the there is a force acting over there, whereas there is another force but in that direction... We need to be more specific. For instance, say that there is a force acting to the inside, and another to the outside.' Even though the use of forces is beyond what it is expected for target students to know, this qualitative description provides a conceptual framework for the group to decide on the physics for the problem."

Finally, after the initial stages that motivated the use of equations or concepts for guiding this decision-making process, all groups selected concepts and procedures by combining information available through equations and data created by them (i.e., initial conditions). Because concepts are expressed through equations, their algebra and physics knowledge allowed them to identify that well-structured problems must mimic the characteristic of a well-defined system of equations (i.e., well-defined system of equations has a unique solution for each variable). By mimicking this process, students utilized variables included in the equations and made decision regarding concept to use as question, and the needed initial conditions for the problem to be well-structured with unique solutions. The following interaction illustrates this process:

> Student F: "We could give them the radius for the barrel, and we also give them a linear speed in m/s, so they have to obtain the angular speed."
>
> Student G: "It would be better if we give them the angular speed and radius, so they can calculate the linear speed. "
>
> Student F: "Yes, that works too."
>
> Student G: "And with the linear speed they could then determine how much distance was covered by the barrel since this was tossed."

The manipulation and decision over the concepts and procedures showed above is made from the relationship between concepts available in the equations, in this case $v = \omega R$, where linear speed is equal to the product of angular speed times the radius. The discussion then turns into a very simple back and forth on whether to use a combination of v and R, or rather ω and R, using the missing piece of information as a question. This process of 'playing' with the concepts available in the equations facilitated the definition of the physics questions to introduce into the problem.

Physics Context and Wording

Teams posed ideas and decided on the contextualization (i.e., place, subjects, actions etc.) and wording of the problem. This process required groups to invest significant time (16% of the data). To interpreting the high percentage, first one could relate this to the freedom to select the phenomena (i.e., daily situations) where circular motion is observed. Groups spent a considerable amount of time and experienced some conflict to find the right contextual elements to use. For instance, in Group 6 (Treatment) they started by only focusing on objects with wheels, but they attempted to achieve some degree of novelty in their ideas by pushing the conversation towards situations beyond wheels (i.e., "Is there one without wheels? I cannot think of anything."), or Group 8 (Traditional) wanted to create something interesting and fun (e.g., "Let us do something cool, like a wooden spinning top.").

An interesting and not that obvious set of examples were provided during this process by all groups, like a fisherman moving his fishing rod and describing a circular motion, or an ant walking on the inner wall of a bottle. Here, originality was controlled by their level of confidence in exploring such situations through their physics knowledge, (e.g., "We do not need to complicate ourselves with that.") and ended up using well-known situations. As seeing in Figure 3, Group 6 (Treatment) selected the wheels of a car moving covering a trip between places; Group 7 (Treatment) decided on the use a person trapped in a barrel in motion; Group 4 (Traditional) decided on the motion of a bicycle; and Group 8 (Traditional) utilized references from a problem created by their instructor to design a situation where Donkey Kong moves a barrel. One may argue that these situations were selected based on familiarity, or because students perceived them as attractive enough to motivate students into solving them.

The wording of the problems illustrate the use of technical language, as well as a certain degree of conceptual (mis) understanding for the appropriate phrasing of the situation. The first conceptual issue one may perceive from the data and the wording of the problem is the confusion between scalar (i.e., quantities defined by a numerical magnitude and measurement unit) and vectors (i.e., quantities defined by a numerical magnitudes, direction and a measurement unit). A simple example emerged from Group 6 (Treatment), where a student asked the following when deciding on the right wording of the problem: "If I want to say that the car wants to move from A to B, is that displacement? " Because displacement is defined as a vector, then to properly use it, the group needs to incorporate a direction. There is no evidence in the data when this correction was made, but the problem is worded in scalar not vector format by framing the phenomena as "a car wants to move."

Another example of negotiating the wording with a correct use of physics concepts was observed in Group 8 (Traditional), when students discussed the conditions under which Donkey Kong would make the barrels move:

> Student P: "For this he tosses the barrel from rest?"
>
> Student O: "You cannot toss a barrel from rest. It releases the barrel then. He let the barrel go."
>
> Student P: "Ah, okay."
>
> Student O: "Or better, he tosses it with an initial speed, is that okay?"

This segment showed students' understandings of motion in connection with an appropriate use of language to convey the idea that releasing and tossing the barrel imply different physical conditions. Here, a body that begin its motion from rest must be release to accelerate due to the presence of an external force (e.g., gravity), and will therefore gain speed. Differently, tossing implied an interaction (i.e., force) that boosted energy and therefore speed to the object that was moving. Both ideas showed comprehension of motion and the implications of forces for the motion defined in the problem.

Discussing Magnitudes and Units

During this process, groups engaged in discussions and decision making regarding the scores and magnitudes, as well as measurement units for the physics concepts (e.g., 10 km/h, 20 s, 2.5 km) to be introduced into the problem's description. This process is important as it brings a sense of 'reality' to the physics of the phenomena and situation under design. Consequently, this process enabled groups to identify and select appropriate numbers to associate with each concepts used as data (i.e., initial conditions). The validity of these magnitudes was tested by solving the problem, and through the calculation of reasonable responses. For instance, Group 7 (Treatment) discussed the appropriateness of high angular acceleration for the barrel that yield to 1,400 complete revolutions in one minute, and decided to 'Lower the values'. Similarly, in Group 6 (Treatment), I observed the following interaction for deciding on the acceleration of the car:

> Student A:"How much do we say the acceleration will be?"
>
> Student B: "20. "
>
> Student A: "20 what? "
>
> Student B: "Meter by square second."
>
> Student A: "Is that too much?"
>
> Student B: "I know it is a lot. Do you want the car to get to its destination fast or slow?"
>
> Student A: "I want to get there normal."

From the latter dialogue, one could notice the intention to utilize magnitudes that reflect real life situations. Later on this process, the same group tested the problem with an acceleration of 10 m/s, and obtained a final speed of 200 m/s, which is clearly unrealistic for a common car moving in the city. Other ways of suggesting and deciding on this magnitudes were not as clear, given that students suggested numbers without clear rationale from where these came from. In addition, the nature of problems allowed me to identified different ways in which data and magnitudes are introduced, as transformation of units and other ways in which data needs to be manipulated in order to be used. Even though problems show clear signs of this process, the data does not provide much evidence on how these decisions were made. The little evidence shown in the transcripts illustrated the decision of using diameter over radius as a way to add complexity to the problem (e.g., "Use the diameter so they believe that this is the radius and get all confused."), or the use of km instead of m, thus including a data transformation that solvers need to address (e.g., "Do we include the transformation from kilometers to meters?" – "No, that is not our responsibility.").

Finally, the lack of evidence regarding the multiple other ways in which data was introduced in the problem may have been a process that groups engaged in silence, or as responsibility of one or two other members who added the final details to the problem, in an effort to make it look more elaborated. It is also possible that such processes occurred during the problem solving session were not captured due to the noise in the room.

4.1.2 Problem Solving Strategies

The following set of themes emerged from students engaging in processes often associated with solving math-based problems, where students are likely to utilize algebraic steps, request information regarding equations and concepts, and enact on physics descriptions connected to the context of the activity. The literature on novice and experts physics problem solvers suggest that the former group tend to utilize algebra-based strategies (e.g., 'plug and chug') rather than qualitative descriptions, a strategy associated with expert behavior (Shing, 2008; Docktor et al., 2015). Accordingly, the presence of these three processes for testing the appropriateness of their physics-related decisions is encouraging as evidence of the time invested on mathematical and conceptual dimension of the generated problem. Consequently, each of these themes has some unique features presented below:

Algebraic Procedures

This process relates to algebraic steps that the group went through to obtain physical quantities as a way of solving the problem and was normally used to justify the appropriateness of the designed problem. This process included suggesting strategies to determine a physics quantity (e.g., "Here we will use a proportionally rule. If one revolution is 2, then x revolutions will be…"); and requesting advice on how to proceed in order to get the right value (e.g., "How to I transform this to radians? Does someone know how to?"). Most of the evidence found here emerged when students wanted to achieve either of the latter two goals.

To contextualize the use of algebra in this context, it is important to remember that kinematics problems rely on three fundamental physical quantities: position $[\vec{r}(t)]$, velocity $[\vec{v}(t)]$ and acceleration $[\vec{a}(t)]$, all functions of time (t). Even though these concepts are defined as vectors, students would normally utilize these mathematical representations to determine scalar quantities, or the magnitudes of the vectors at any given time. In circular motion these concepts are written in an angular form: angular position $[\theta(t)]$, angular speed $[\omega(t)]$ and angular acceleration $[\alpha(t)]$. Figure 4.2 depicts the set of equations students drew on in order to solve circular motion problems. The last four equations connect linear with angular concepts, and emerged as useful relationships for addressing this type of motion. The majority of the problems and situations addressed in this particular learning context involved situations where the magnitude of acceleration was either zero, or a non-zero constant acceleration.

Linear Concepts

Position: $r(t) = r_0 + v_0 t + \frac{1}{2} a t^2$

Speed: $v(t) = v_0 + at$

Angular Concepts

Angular Position: $\theta(t) = \theta_0 + \omega_0 t + \frac{1}{2} \alpha t^2$

Angular Speed: $\omega(t) = \omega_o + \alpha t$

Connecting Linear with Angular Concepts

Arch length: $d = \theta R$; (R) is radius

Tangential Speed: $v = \omega R$

Tangential Acceleration: $a_t = \alpha R$

Centripetal Acceleration: $a_c = v^2/R$

Figure 4.2: Mathematical representations for kinematics concepts on their linear and angular form.

In order to test their problems, students manipulated some or all of the equations shown in Figure 4.2. For instance, students in Group 8 (Traditional) had the following argument to determine the angular position of distance covered by the barrel:

> Student L:"And how would I get the angle?"
>
> Student M: "With the (angular) acceleration that is obtained from the equation. With the angular speed. Because you have the angular speed at 3 s, which is 10 π, so 10 π is equal to (angular) acceleration plus the initial angular speed. So then you clear and get the (angular) acceleration."

The first thing one should notice is that student M suggested the use of angular speed $[\omega(t)]$ at time 3 s, to determine the value of angular acceleration by isolating this value from the equation, because all other elements were given. Once this was done, the argument, although not explicitly mentioned, oriented to the use this value of angular acceleration into the equation for angular position, and calculate θ at 3 s. Once again this was possible because all other elements in the equation are defined. The definition of algebraic strategies happened across the data. Another interesting example was observed in Group 6 (Treatment), as they used the equations $r(t) = r_0 + v_0 t + 1/2 a t^2$ and $v(t) = v_0 + at$ to determine the time that it would take the car to reach its destination.

In connecting with these set of linear representations, they utilized the fact that the car and a given point in the edge of the wheel would have the same tangential (i.e., linear) speed. The following interaction depicts the set of algebraic steps suggested for one member to achieve this goal:

> Student A: "So we have that the initial position is zero, and the initial speed is zero. And we have that (in the equation), only the acceleration for the square time will remain."
>
> Student B: "And then?"
>
> Student A: "That will give you ten m/s (magnitude of the acceleration) times the square time, and with that you can obtain the time. So, it will be the square root of something, and then we used only the positive root."

This interaction shows an appropriate use of equation $r(t) = r_0 + v_0 t + 1/2at^2$ to obtain the time, given that all the elements but the time are known (final distance is given in the heading of the problem and is equal to 2 km). Because mathematical manipulation may be perceived as a rather individual exercise, it is not surprising that the audio recording would only capture brief descriptions of the strategies to be implemented to find numerical values, and the request for advice on how to calculate them. Thus, providing no data on the complete implementation of these algebraic procedures. An alternative, and plausible explanation may regard the errors associated with data collection.

Physics of Circular Motion in Context

This theme is observed when groups engaged in qualitative description of the physics regarding the circular motion in the context under consideration for the problem. This process enabled access to students' conceptualization of the physics phenomena in question and the ways in which they would explain such situations. The sample size of examples that illustrate this process is rather small and does not provide evidence on the most difficult concepts. Consequently, the reduced frequency of observation reflects the disparity between algebraic versus qualitative strategies students would display when addressing well-structured problems, and even though the activity is ill-structured, the requirements may motivate students to prioritize reflection of equations for over conceptual descriptions. Moreover, qualitative descriptions emerged from the data when students tried to make sense of the situations and physical objects considered for the problem. Among the concepts described in such a way, there is evidence that students attempted to explain revolutions, tangential velocity and inertia, this last used to determine what would happen if someone gets loose from a fast spinning carrousel.

The concept of a revolution was conceptualized through the perimeter of a wheel: " Suppose that first there is a point that moves along the perimeter until here. That will be one revolution." This description is very simple and does not really reflect deep understanding of a physics concept that one were to associate with motion. A more interesting example was provided by Group 8 (Treatment), in an attempt to understand the relationship between angular and linear speed (e.g., $v = \omega R$) in the context of a wheel moving. First, the concept of angular speed was defined as the change of angular position per unit of time (i.e.., $\omega = \Delta\theta/\Delta t$), and may be difficult to understand because it does not imply distance units like meter or kilometer like most of the concepts teach on kinematics. Secondly, and because this concepts did not involve longitudes, an object spinning will measure the same angular speed at any distance from the center of rotation (i.e., radius) at a particular time. However, the linear or tangential speed will increase according to the distance from the center of rotation as shown by the equation. Next, the discussion unfolded as follow:

> Student E: "Why? If this is supposed to be in the same Wheel. So, if you advance five meter you will complete the same number of revolutions than here."
>
> Student G: "Yes, you are right. So, how many..."
>
> Student F: "The angular speed will change at different points of the wheel."

As one would notice, the claim made by student F suggested a misconception regarding the nature of angular speed, because this quantity remains constant regardless of the distance from the center of rotating object. Consistent with the definition of angular speed, the comment made by student A would have made more sense if instead of using 5 meters as the distance covered, he would have used angular measurements to highlight the distinction with linear speed. The last example that illustrates the nature of qualitative descriptions used by students emerged in Group 4 (Traditional) when discussing the nature of acceleration and forces on circular motion:

> Student S: "There is also velocity, this velocity that goes to the middle. This is the one that enables... This was related to forces if I remember. The topic of the two forces pointing out to one side. Now I remember, centripetal and centrifugal force."
>
> Student T: "Centrifugal force was like..."
>
> Student U: "There is one that pints inside."
>
> Student T: "No.
>
> Student S: "Centripetal force points to the inside."
>
> Student T: "Okay, centripetal force points to the inside. But centrifugal points to the outside. And those two forces would make that... "There were like equals and... "

Student U: “Both forces allow the circular motion.”

Student T: “But this centrifugal force was something like hypothetical, or something that was not real…”

According to the interaction, students attempted to make sense of the elements involved in the study of circular motion by discussing the physical interactions that enable such motion, here centripetal force. The ideas related to centripetal force are correct: it is an interaction that is directed to the center of the circumference described by the motion, and it is responsible for the circular motion. However, centrifugal force, as corrected by student T at the end of the interaction, is not a force but rather the effect of inertia, defined as resistance to change the state of motion and is often referred to as a “fictitious force.“ This resistance is perceived any time an object experiences an external force that produces an acceleration. We may be all familiar with the fact that when an object is moving in a circular motion, there experience “something” pushing the object to outside, as if this were to be ejected. That “something” is the effect of inertia, and nature’s resistance to any change in motion, and willingness for objects to move in a straight line. Finally, this interaction provides some insights on students’ understandings, but again fall short to give substantial evidence to assess whether students are actually understanding the underlying physics of circular motion beyond the use of equations.

4.1.3 Team Process Comparison

To end result section 1, here I present a group level comparison based on the percentage of observed themes by each group. With this I intend to illustrate the time invested on these different themes for generating a physics problem. To do so, I used the frequency of observation for each theme, and determine the relative frequency per group, which are depicted on Figure 4.3. To add reference, the black dotted line represents the average percentage.

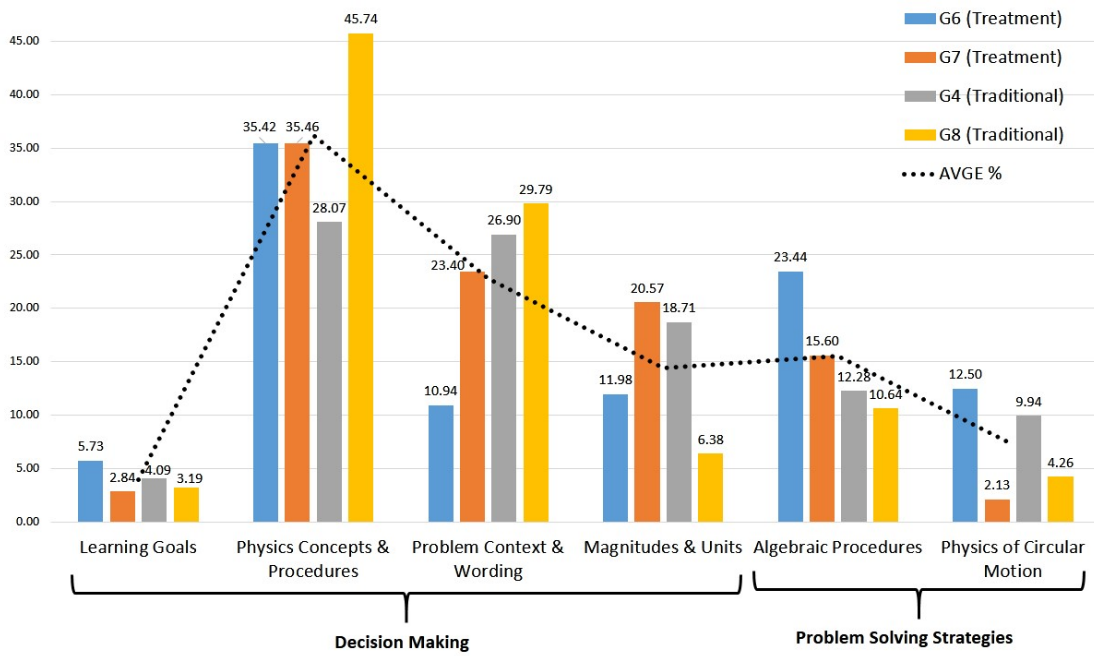

Figure 4.3: Percentage of observed theme frequency by group.

By simple scanning the visual representation, it is possible to see that decision making processes demanded higher investment than problem solving strategies. Within the first category (decision making), groups engaged in learning goals about the same, with Group 6 being the one that stands out from the rest. In terms of physics concepts and procedures, being this the process were teams spent most of their time, it is evident that both groups form the Treatment section invested about the same percentage on deciding the physics with around 35.5% of their effort, whereas Group 8 (Traditional) invested ten percent more on this process. Further, deciding on the context of the problem is one of the categories where I observed most disparity across groups, with groups from the Traditional section engaging in this process consistently more than Treatment groups. On magnitudes and units, Group 7 (Treatment) and Group 4 (Traditional) are the ones that spent close to 20% of their time on discussing this topics.

The algebraic dimension for solving the problem shows also diverse engagement, with only Group 6 (Treatment) spending time above the mean. Regarding the time spent on algebra one must be cautious, because there may be the case that students engaged in such process in silence. Consequently, one may say that students in Group 6 verbalize in higher rate their mathematical procedures compared to the rest of the sample. Finally, qualitative descriptions of the physics in context shows a similar trend than algebraic procedures, with the exception of Group 7 (Treatment), a team that only engaged in this process 2.13% of their coded data.

Finally, this evidence encourages the use of ill-structured activities, and more specifically the task of creating problems, as because student groups would consistently spend more time on addressing the multiple dimensions where decision must be made, and thus prioritizing process of idea-generation. Moreover, the extent to which the percentage of engagement leads to better results in terms of the quality of the problem would strongly rely on the effectiveness of these processes, and overall collective performance. However, having evidence that students would dedicate significant portions of their time in generating ideas for the creation of problems, or solutions in general, is likely to boost familiarity in the face of idea generation using concepts and principles of the curriculum, which may ease transfer and the development of deep learning.

4.2 Student-Generated Problems

In this section I dissect the characteristics of the problem created by student groups from three different sections of the physics course at the university. First, let us remember that the activity student faced consisted of creating a physics problem about circular motion for high school students. The activity explicitly stated that problems should be designed as contextualized learning activities for high school students, without direct guidelines on the type of physical situation, concepts, nor number of questions to include in its description, all dimensions decided on and designed by each group.

The qualitative description of the problems presented below emerged from identification of attributes that enable a characterization of the learning activities designed by student groups. Here, and as described in the methods section (see Table 3.2, in Chapter 3), I focused on different variables that might shed light onto the problems' details, complexities and challenges, all aggregated in a variable labelled as 'problem elaboration'. Among these variables I defined: Contextual Details of the problem (i.e., the degree to which problems include contextual elements that facilitate readers and solvers to imagine the situation as a real-life scenario, with actors witnessing or engaging in actions related to the physics phenomena under study); Word Count (i.e., as a an alternative approach to the degree of elaboration of the problem); Physics Concepts Asked; Problem's Cognitive Demand (i.e., taken from a taxonomy of introductory physics problems built by (Teodorescu et al., 2013); and the Type of Information presented in the problem, where I identified Ready-to-Use Information (i.e., data in the problem is explicitly presented in the problem and with the appropriate measurement units for its use in the equations of circular motion) and Assumptions (i.e., problem forces students to assume particular characteristics of the problem, such as constant acceleration, or the position of the 'particle' that describes the circular motion). The alternative to the mentioned types of information is what I called Required Treatment Information, consisting of data presented in the problem's description, yet, it cannot be use directly on its current form, and thus requires treatment or transformation. In this category of information, I identified characteristics such as Conversion of Units; Text to Math Representations (i.e., physics information is presented in written form that needs translation into mathematical expressions. For instance, 'begin its motion from rest' or 'uniform motion'); Algebraic Transformation (i.e., when the physics information needed to solve the problems is 'hidden' in a concept or magnitude, and requires algebraic steps in order to solvers to access and use it); and finally Information Research (i.e., the problem is designed in such a way that solvers must conduct some degree of research in order to solve the problem).

A second dimension of analysis I deemed important for characterizing student groups' problems, focuses on the physics concepts used as questions. Through this analysis, I provide evidence of the frequency of the physics concepts asked, and the plausible interpretation that a higher frequency may be a reflection of their understanding of the concept, as well as their familiarity, both being perceived as consequence of a high usage in their respective sections. Finally, results are presented first to characterize problems within each class on the mentioned dimension, and then aggregated to draw differences and similarities in the problems designed by groups across classes.

4.2.1 Traditional Section

The instructors of the traditional section implemented lecture-based instruction to address physics curriculum, while utilizing textbook problems once per week during solving sessions. During these sessions, and similar to the strategy engaged by instructor in the Mixed section, professor behaved as a source of information, that is, provided direct responses to students' questions.

Physics Variables

In Table 4.2, I show the physics variables asked about in the learning activities made by groups on Traditional section, the frequency and percentage of use in descending order. From the 10 problems developed, groups designed problems oriented to ask ten physics concepts, for an aggregated value of 2.9 different variables per problem. According to the list and percentage of use, tangential speed, centripetal acceleration and angular speed are the three physics variables most frequently used in questions, accounting for 48.2% of the variables asked within the sample. Following, tangential acceleration, time and frequency account for similar 10.3% of concepts asked, whereas angular acceleration and linear distance covered the least asked variables.

Table 4.2: Physics variables asked about in problems designed by student groups in Traditional Section.

Physics Concepts	Frequency	% of Use
1. Tangential Speed	5	17.2
2. Centripetal Acceleration	5	17.2
3. Angular Speed	4	13.8
4. Tangential Acceleration	3	10.3
5. Time	3	10.3
6. Frequency	3	10.3
7. Period	2	6.9
8. Angular Distance Covered	2	6.9
9. Angular Acceleration	1	3.4
10. Linear Distance Covered	1	3.4
11. Position	0	0.0
12. Number of Revolutions	0	0.0
Total	29	100

Among the pieces of information provided in the problems as data, time, angular speed, frequency and angular acceleration account for 55.17 % of the information given to solve the problem. Problem in this section showed the tendency to ask information regarding different forms of speed and acceleration. The most frequent concepts used by groups in this section were related through multiple mathematical expressions, thus, calculating them would require a larger number of algebraic steps. For instance, tangential speed $v_t = \omega R$, where $\omega = 2\pi = \omega_0 + \alpha t = \Delta\theta/\Delta t$ (different representations for angular speed ω). Consequently, problems in this group might require better understanding and comprehension of the multiple representations and principle governing circular motion.

Problem Characteristics

Figure 4.4 shows a radial representation of problem characteristics for elaboration. Again, the dotted black line represents the average score. A difference from figure 1 is that, in this case, I have included Matching as the highest Cognitive Level coded by one problem in this group (G1), while all problems required Comprehension and Symbolizing, and the reason why these are not included in the figure.

The graph (Fig. 4.4) shows the tendency for problems in this section to score higher on the variables located at the left side with the exception of matching. The type of information included in these set of problems is mostly Ready to Use Info, with a mean of 1.4 pieces of information per problem, whereas Required Treatment categories average .5 (Conversion of Units), .0 (Information Research), .9 (Text into Math Representations) and .9 (Algebraic Transformation). According to the figure, Group 6 (G6) is the group with the highest score in the Ready to Use Info attribute. For Conversion of Units, six of the ten problems include this type of information once, while no group utilized Information Research as a condition for its solution. Problem from Group 4 (G4) includes two elements that require translating from text into math representations, while others one or zero. Algebraic transformation have similar range (0-2) with Groups 2, 3 and 9 the ones with 2 pieces of information that required this type of treatment. Similar range is observed for Assumptions, with groups 1, 2, and 4 the ones that demand at least two assumptions.

The number of physics concepts asked about ranges from 1 to 5, with problems asking almost three values per problem (Mean = 2.9), and requiring a similar number of equations per solution (Mean = 3.4). On these two and highly related dimensions,

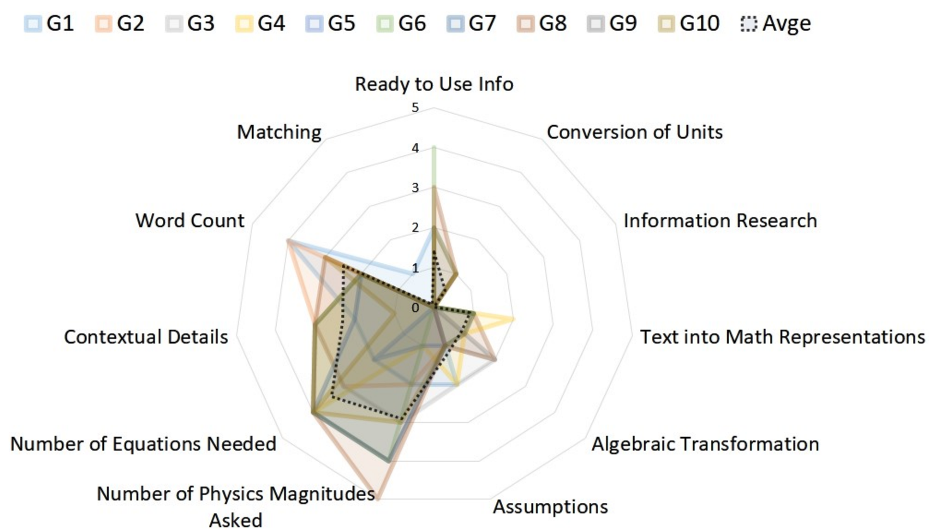

Figure 4.4: Problem Characteristics in Traditional Section.

problems from groups 6, 7 and 9 used four physics magnitudes, while the activity from group 8 includes five. Moreover, to solve the problems from the mentioned groups (G6, G7, G8 G9), solver will need at least four equations determine the value of the magnitudes asked.

For Contextual Details, problems from this section included at least two elements for either location, subjects or actions (Mean = 2.3). Six out of the ten groups working on this section included the three elements for context (G2, G3, G4, G6, G8 G9), while group 5 had zero. Interestingly, the contextual details does not necessarily show the number of words (Word Count) in the problem's description according to the quartile scale used. In this dimension, groups 1 (94 words) and 2 (91 words) are located in the 4th quartile (score 4), while the other groups with three contextual details show 54 (G3), 52 (G4), 39 (G6), 74 (G8) and 54 (G9) words, and are placed in the 2nd (G3, G4, G6 G9) and 3rd (G8) quartile with the respective score.

Example of Physics Problem from Traditional Section

Based on the problem attributes described above, the learning activity designed by group 8 is the one with higher elaboration, and presented in Figure 4.5. This problem includes contextual details, such as subjects and actions, along with questions that tackle the angular distance covered, centripetal and tangential acceleration, as well as frequency and period. The originality of the problem comes from story elaborated to define the situation, as well as the use of angular distance covered, as one of the least asked physics magnitudes within the sample of problems from Traditional section.

Problem by Group 8
Donkey Kong wants to throw barrels to King K Rool. For this throws one with an angular speed of 2π rad/s. By knowing that at 3 s its speed is 10π rad/s, and that the barrel impacts at 5 s, determine: a. the angle covered by the barrel; b. the magnitude of the centripetal and tangential acceleration at the moment of impact at 6 cm from its center; c. frequency and period.

Type of Information
Ready to use information: angular speed of 2π rad/s; time 3 s; time 5 s.
Requires-Treatment information:
- Conversion of units: Radius from cm to m.
- Research: NA
- Translate text into math expressions:
- Algebraic treatment: NA

Assumptions: Initial conditions are consider at time 3 s, rather than 0 s as in other problems; $\theta_3 = 0$ rad as the initial angular position of interest in the barrel at 3 s.

Solution Description
Because no angular acceleration is given, solvers can use:

$$\omega(t) = \omega_o + \alpha t$$

At 3 s as initial condition to determine the magnitude of α. Later, to answer question a. (angle covered at 5 s) solvers must utilize:

$$\theta(t) = \theta_o + \omega_o t + 1/2\alpha t^2$$

By plugging the appropriate magnitudes for time (5 s), initial angle at 3 s, and angular speed at that time. To calculate the magnitudes of centripetal and tangential acceleration (question b.), students need to use $v = \omega R$, with radius in meters. With the magnitude of tangential speed, the can plug into:

Centripetal acceleration: $a_c = -\frac{v^2}{R}$; Tangential acceleration: $a_t = \alpha R$

Finally, period and frequency can be calculated with

$$\omega = \frac{2\pi}{T} = 2\pi f$$

Figure 4.5: Problem example, type of information and solution description from Traditional Section.

4.2.2 Mixed Section

According to the description of the teaching and learning strategy followed in this section, students faced lecture-based instruction, along with the use of textbook and ill-structured problems every other week during scheduled problem solving sessions. Moreover, during these sessions, instructor showed the tendency to provide direct information when students requested it, engaging in the same strategy for sharing information than instructor in Traditional section.

Physics Variables

In Table 4.3 I show a list with the physics variables used as questions on the problems designed. The next columns show the frequency and percentage in which concepts are requested in descending order. Of the 9 problems created, a total of 11 different physics variables were used is questions, with angular speed as the one with highest frequency, while angular acceleration, position, centripetal acceleration, distance covered, angular distance and time were the least used. In average, problems created in this section have fewer than three questions (M = 2.7). A higher number of problems asked for angular speed, period and frequency, three concepts whose definitions are intertwined through the following mathematical expression:

$$\omega = 2\pi/T = 2\pi f \tag{4.1}$$

Where T is period and f frequency. Consequently, 42% of the physics concepts asked could be determined through simple algebraic steps. Now, by paying attention to the physics concepts introduced in the problem as data, I noticed that 30.77% of these pieces of information corresponded to time, and the same percentage regards to angular position as a function of time, angular speed, frequency and number of revolutions combined. In total, more than 60% of the information provided in the problems to find solutions relates to angular distance and time, or a combination of these.

Table 4.3: Physics variables asked about in problems designed by student groups in Mixed Section.

Physics Concepts	Frequency	% of Use
1. Angular Speed	5	20
2. Period	4	16
3. Frequency	4	16
4. Number of Revolutions	3	12
5. Tangential Speed	3	12
6. Angular Acceleration	1	4
7. Position	1	4
8. Centripetal Acceleration	1	4
9. Linear Distance Covered	1	4
10. Angular Distance Covered	1	4
11. Time	1	4
12. Tangential Acceleration	0	0
Total	25	100

Problem Characteristics

In Figure 4.6 I show the characteristics of the problems created by nine student groups in section 2, using the variable attributes described above. In clock-wise direction, the radial representation shows the different forms of information used in the problem, and the degree to which the created activities have Ready to Use Information, or that data requires Conversion of Units, Information Research, translate Text into Math Representations, Algebraic Transformations, or Assumptions. Later, the other half of the graph depicts additional problem attributes associated with the Number of Physics Magnitudes Asked, Number of Equations needed for solving the activity, Contextual Details and Word Count. Notice that I included the average (dotted black line) as a reference. Further, the coding process for problem's cognitive demand showed that all problem were categorized as demanding Comprehension and Symbolizing, and therefore no need to include these attributes into the graphical representation.

Accordingly to the information in figure 1, problems generated in section 2 showed diverse characteristics. First, and due to the different attribute scales, problems' characteristics are unsurprisingly weighted towards the left side of the image. In terms of type of information, Ready to Use Information is utilized in average once (Mean = 1.1), with only two groups (G4 and G8) implanting it above its mean. The most used type of information are Conversion of Units and Assumptions, both with a mean of 1.44 times. For conversion of units, G3 showed the higher use with a count of 3 times, while G6 showed the same count (3) for assumptions. Further, neither problem in this section included data that required Information Research. Translating information from Text into Math Representations is used almost once per group (Mean = .78), and similar to data that requires Algebraic Treatment (Mean = .89).

The number of magnitudes asked in the problems ranges from 1 to 5 with an average of 2.78. G7 is the one with higher number of physics magnitudes asked with 5, followed by G3 and G9 with 4 magnitudes each. Later, the Number of Equations Needed shows the same average that the physics magnitudes asked (Mean = 2.78), ranging from 1 to 4. Here, problems generated by G2, G7 and G8 are the ones that required the higher number of equations, while problem from G9, although asks for 4 physics magnitudes, these can be found through 2 equations.

Later, Contextual Details, such as locations, subjects and actions shows a mean of 1.44, with two groups (G2 G5) not including neither in their problem descriptions. Here, groups G3, G6 and G8 added up to three contextual details for generating their respective problems. This is consistent with the quartile location measured across the sample of problems from the three sections for Word Count. Accordingly, problems from G3, G6 and G8 are located in the 4th quartile (score 4) with a respective count of 91, 82 and 89 words per problem, while the section's mean is 51.1 words (Quartile Score Mean = 2.22).

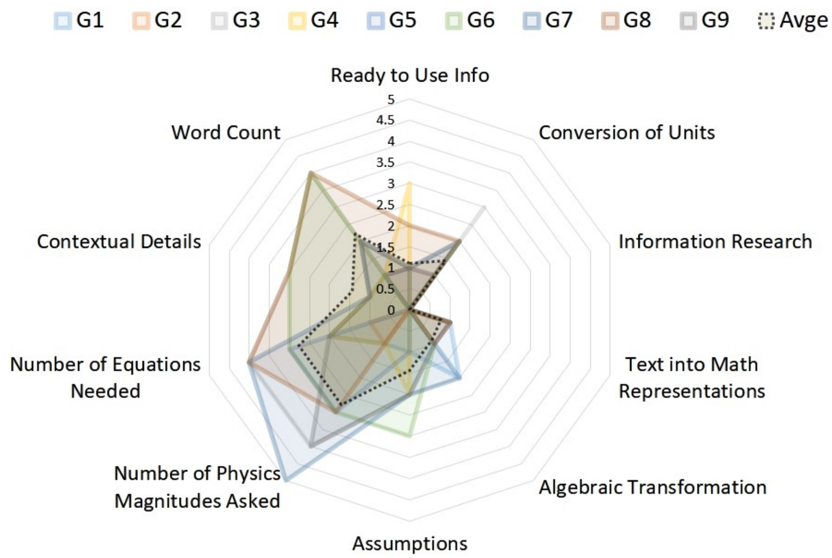

Figure 4.6: Problem Characteristics in Mixed Section.

Example of Physics Problem from Mixed Section

The attributes presented above enable dissecting the nature and elaboration of the problems generated by different groups from Mixed section. Here, I select and show (Fig. 4.7) the most elaborated of these learning activities taking into consideration the sum of the problem characteristics described above, in order to show the description of the problem, type of information, as well as possible solution path to the problem. The elaboration of this problem can be perceived from the physics concepts used as questions and their percentage, with a. time, 4%; b. angular speed, 20%; c. number of revolutions, 12%; and d. tangential speed, 12%, but as a vector in velocity, as well as its contextual details, and different forms of information included as data.

Problem by Group 3
A bus starts from rest after picking up passengers to take them to their destination 1.5 km from starting point. The wheels of the bus have an 80 cm of radius and this travels with a constant acceleration of 2 cm/s^2. With the above information respond: a) How long does it take to get to its final destination? b) What is the wheel's final angular speed? c) How many complete revolutions did the wheel make to reach its final destination? d) What is the value of the tangential velocity?

Type of Information
Ready to use information: NA.
Requires-Treatment information:
Conversion of units: Distance from 1.5 km to m; tangential acceleration from cm/ s^2 to m/ s^2; Radius from cm to m.
Research: NA
Translate text into math expressions: 'bus starts from rest…' means that $\omega_o = 0$ rad/s.
Algebraic treatment: Angular acceleration is must be determined through $a_t = \alpha R$
Assumptions: The position of interest is at the edge of the bus' wheel; value for θ_o as the initial position of interest in the wheel.

Solution Description
Solvers must identified that the movement of interest is the one followed by any point in one of the bus' wheels. And because there is a linear acceleration, it means that there is an angular acceleration governing the circular movement. The bus begins its motion from rest, therefore, $\omega_o = 0$ rad/s. The problem states the final linear distance covered by the wheel, therefore it is possible to obtain the number of revolutions taken during the distance 1.5 km (transformed to meters) by dividing this by the perimeter, which is the longitude of the circumference (question c.). This value (number of revolutions) can be then multiplied by 2π rad, as a way of obtaining the angle covered in the whole motion, or θ_{Final}. Later, by knowing this magnitude, solver can use:

$$\theta_{Final}(t) = \theta_o + \omega_o t + 1/2\alpha t^2$$

To solve for t and determine the time that takes the wheel to cover the distance (question a). Before attempting to solve this, they need to transform the linear acceleration (transformed to m/s^2) given into angular acceleration through the following relationship: $a_t = \alpha R$, and assume a value for θ_o as de position of interest in the wheel. Once the final time is obtained, solvers can use:

$$\omega(t) = \omega_o + \alpha t$$

To determine the angular speed at that final time (question b). Finally, to determine the final tangential velocity (vector) (question d.), solvers can plug appropriate magnitudes for final time (angle and angular speed) into the following equation:

Figure 4.7: Problem example, type of information and solution description from Mixed Section.

4.2.3 Treatment Section

Teaching and learning instruction in Treatment section was based on a combination of lectures and active learning strategies, the latter mainly implemented during weekly problem solving sessions, where student groups worked on ill-structured physics problems. In addition, instructor adopted the role of facilitating student-student interactions by guiding them towards their peers in the face of questions. In detail, and as mentioned earlier in this work, instructor in this section responded to students' questions by pointing out to other students in the class that may know the answer to the original question, or that may have useful information regarding the issue in question. With this strategy, the instructor stops acting as the source of information, and instead focuses on mapping the social system of the class beyond who is connected to whom, but rather as who knows what.

Physics Variables

In Table 4.4 I show the physics magnitudes used as questions in the seven groups in this section, along with frequencies and percentage of use. A total of nine different physics concepts were utilized, for a total of 18, meaning that every problem includes almost three magnitudes as questions (Mean = 2.6). The most frequently used concept asked is number of revolutions (22.2%), followed by angular and tangential speed (16.7% each). Angular distance, time, period, tangential speed, position and frequency are only asked once, while angular acceleration and centripetal acceleration were never included as questions. Here, angular distance and the number of revolutions are two directly connected magnitudes, as in order to know the number of revolutions completed at a given time, students must know either the linear distance covered, or the angular distance, and then divided by perimeter or the angle of one revolution (2) respectively. Based on the physics concepts provided as data for solving the activity, time (5, 20%), tangential acceleration (4, 16%), angular acceleration (3, 12%), diameter and angular position (3, 12% each) are the most frequent concepts. Therefore, it may be fair to suggest that the number of revolutions is likely to be solved using angular rather than linear magnitudes.

Similar to problems in Traditional section, these set of learning activities attempt to add higher number of algebraic steps and physics relationships than the aggregated physics magnitudes in the Mixed section, which were mostly designed to determine angular speed, frequency and period.

Problem Characteristics

In Figure 4.8 I show the problem characteristics for the set of learning activities created by groups in section CR. Again, the black dotted line in the radial graph

Table 4.4: Physics variables asked about in problems designed by student groups in Treatment Section.

Physics Concepts	Frequency	% of Use
1. Number of Revolutions	4	22.2
2. Angular Speed	3	16.7
3. Tangential Speed	3	16.7
4. Frequency	2	11.1
5. Linear Distance Covered	2	11.1
6. Position	1	5.6
7. Tangential Acceleration	1	5.6
8. Period	1	5.6
9. Time	1	5.6
10. Angular Distance Covered	1	5.6
11. Angular Acceleration	0	0
12. Centripetal Acceleration	0	0
Total	18	100

represents the average score for every variable included in the analysis. Similar to the description of problems' attributes from section BP, figure 1 includes Matching as the higher cognitive level that is different across problems in the sample, because every problem was coded as requiring Comprehension and Symbolizing. In detail, the problem from group 5 was the only one that included matching physics magnitudes and principles.

For the type of information used as data in the problems, problems include almost two (Mean = 1.86) pieces of information that are ready to use, bring group 7 the one that introduced up to four of such type of data, in contrast with groups G5 and G6 that used non. In the dimension of information that requires treatment, groups G3 and G6 include two pieces of data that require Conversion of Units, while the across the sample this type of information treatment is less than one per problem (Mean = .86). Only G5 introduced conditions that demanded Information Research in their problem. Further, translating Text into Math Representations is, along with information research, the second less used information treatment required for solving the problems, and introduced once by groups G4, G5 and G6. Finally, problems in this section showed less than two Assumptions per group (Mean = 1.43), with problems from groups G1, G3, G5 and G6 requiring solvers to make two assumptions regarding motion and the position of interest.

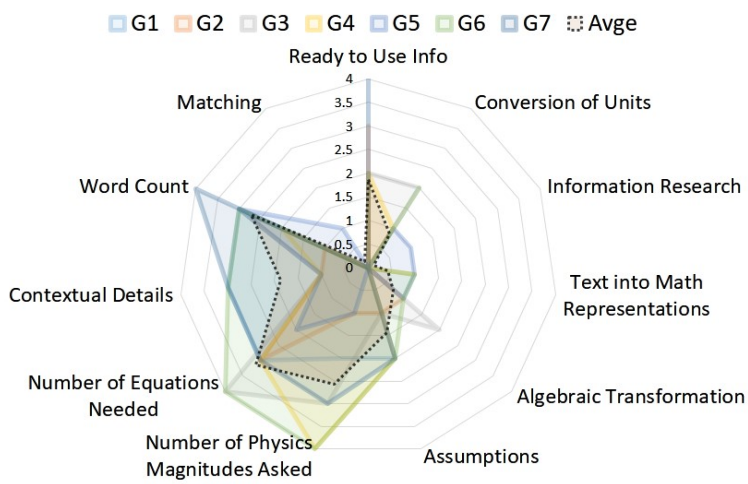

Figure 4.8: Problem Characteristics in Treatment Section.

In average, problems from this section asked for less than three physics magnitudes per problem (Mean = 2.6). This problem characteristic ranges from 1 to 4, being groups 4 and 6 the ones that included up to four physics concepts as questions in their problems. Similarly, the number of equations needed to solve these problems is in average three (Mean = 3.1), with activities from groups 3 and 6 needing up to four mathematical representations of physics concepts and/or principles for reaching solutions.

Finally, groups from this section used less than two Contextual Details such as location, subjects or actions in their problems (Mean = 1.9). Every learning activity created here included at least one contextual detail, with problems generated by groups 1, 6 and 7 including up to three (location, subjects and action). In terms of Word Count, group 7 shows the highest with 89 words, and falling into the 4th quartile (score 4), followed by groups 1 (79 words), 3 (56 words), 5 (56 words) and 6 (79 words), all located in the 3rd quartile (score 3).

Example of Physics Problem from Treatment Section

According to the elaboration of the problem, that is, accounting for the scoring on each of the used attributes mentioned above, group 6 created the problem with higher elaboration among the section (Fig. 4.9). This activity included three contextual elements in subjects, actions and location to enable solvers' imagination into the problem they are facing, as well as a relatively long description of the situation and the four questions to solve. In terms of physics concepts, this activity asks for tangential speed, angular speed, angular distance, and the number of revolutions completed.

4.2.4 Section Comparison

The following sub-section of analysis and results aims to compare the problem characteristics of the three sections, on the same dimensions described so far: Physics concepts used and characteristics.

Physics Variables

In Figure 4.10, I present the average use of physics concepts by sections and the type of circular motion (i.e., uniform or accelerated) that describes the phenomenon used for the problem. The dotted black line represents the average use of physics principles accounting for the 26 problems included in the sample (Traditional: 10; Mixed: 9;

Problem by Group 6
A person on his/her car wants to move from university campus to city downtown, a trajectory of 2 km in longitude. The car starts from rest with a constant acceleration of 10 m/s^2. If the car wheel has a radius of 30 cm: a) what is the wheel's final tangential velocity? b) What is the wheel's final angular speed? c) What is the final angular distance? d) Determine the number of complete revolutions made by the wheel.

Type of Information
Ready to use information: NA
Requires-Treatment information:
Conversion of units: Radius of 30 cm to m; Distance from km to m.
Research: NA
Translate text into math expressions: The car starts its motion from rest, that is $\omega_o = 0$ rad/s
Algebraic treatment: Transform tangential acceleration to angular acceleration with $a_t = \alpha R$
Assumptions: The position of interest if located at the edge of the car's wheel; Value for $\theta_o = 0$ rad as the initial position of interest in the wheel.

Solution Description
Solvers must identified that the movement of interest is the one followed by any point in one of the car's wheels. And because there is a linear acceleration, it means that there is an angular acceleration governing the circular movement. The car begins its motion from rest, therefore, $\omega_o = 0$ rad/s. The problem states the final linear distance covered by the wheel, therefore it is possible to obtain the number of revolutions taken during the distance 2 km (transformer to m) by dividing this by the perimeter (R in m), which is the longitude of the circumference (question d.). This value (number of laps) can be then multiplied by 2π rad, as a way of obtaining the angle covered through the entire motion, θ_{Final} (question c.).
Later, by knowing the final angular position obtained above, solvers plug it into:

$$\theta_{Final}(t) = \theta_o + \omega_o t + 1/2\alpha t^2$$

To solve for t and determine the time that takes the wheel to cover the distance. Before attempting to solve this, they need to transform the linear acceleration given into angular acceleration through the following relationship: $a_t = \alpha R$, and assume a value for θ_o as de position of interest in the wheel. Once the final time is obtained, solvers can use: $\omega(t) = \omega_o + \alpha t$

To determine the angular speed at that final time (question b). Finally, to determine the final tangential velocity (vector), solvers can plug appropriate magnitudes for final time (angle and angular speed) into the following equation:

$$\vec{v}(t) = \omega(t)R(-sin\theta(t)\hat{\imath} + con\theta(t)\hat{\jmath})$$

Figure 4.9: Problem example, type of information and solution description from Treatment Section.

Treatment: 7). Across the sample, the number of problems with constant angular speed is the same as the number of problems based on accelerated circular motion (13). This count is slightly different y sections, where groups from Mixed section preferred to address uniform circular motion (6) for over its version with constant acceleration (3). The opposite is observed in Traditional section, where 6 of the 10 problems focused on the accelerated circular motion. Finally, problems in the Treatment section problems address uniform motion (3) and accelerated motion (4).

According to the mean and radial graph, the three sections display similar shapes, with the higher observed variations for physics magnitudes such as number of revolutions (Traditional = .0; Mixed = .3; Treatment = .6), centripetal acceleration (Traditional= .5, Mixed = .1; Treatment = 0), and period (Traditional = .2; Mixed = .4; Treatment = .1). One would expect that sections addressing the same curriculum in parallel would using similar set of concepts. Yet, the small differences in the frequency of concepts introduced might be a consequence of instructors' emphasis over a set of concepts for over others, which may influence over students' familiarity and comfort for manipulating a particular set of concepts compared to others.

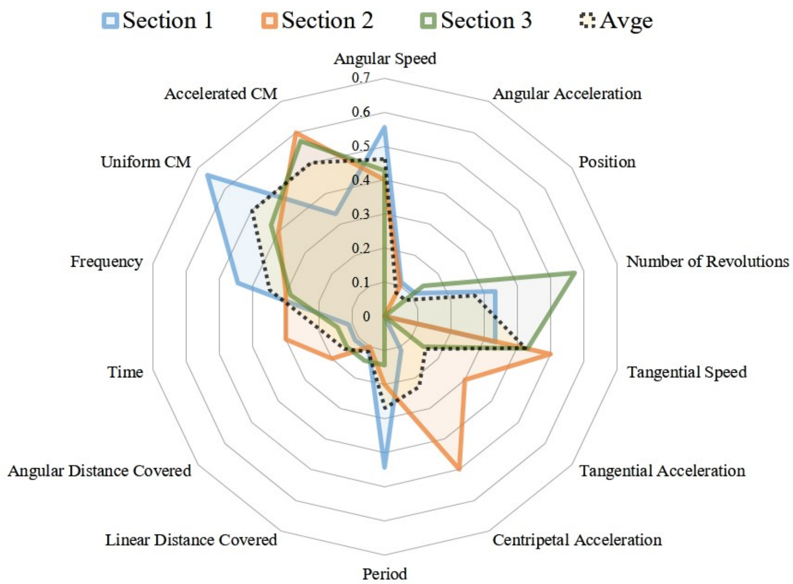

Figure 4.10: Average use of Physics Concepts and type of Circular Motion included in Problems by Section.

Problem Characteristics

In Figure 4.11 I followed similar procedure than for generating Figure 4.10, and aggregated the average score for problems' characteristics by section. In order to do this, I first standardized each variable included as problems' attributes, that way allowing only one scoring scale. Accordingly, every variable has a mean of zero and a standard deviation of one. As a reference, Figure 13 includes the average across sections (dotted black line). Here, I included a variable called *Problem Elaboration*, which represents the sum of the standardized scores for every attribute variable found to characterize student problems.

A first observation of the distribution of characteristics across sections, it is possible to identify the areas where sections may have emphasized above others. For instance, groups from Treatment section (.34) included, in average, more ready to use information that students from Traditional (-.02) and Mixed (-.24) respectively. Similarly, conversion of units is requirement used more by group from Mixed (.59) than the others, whereas information research appears once in section Treatment (.54). Translating text into math representations is a type of data use more by groups from section Traditional (.32) compared to others. In addition, algebraic treatment (Traditional = .06; Mixed = .05; Treatment = .1) and assumption making (Traditional = -.19; Mixed = .12; Treatment = .1) are observed at fairly similar level across sections.

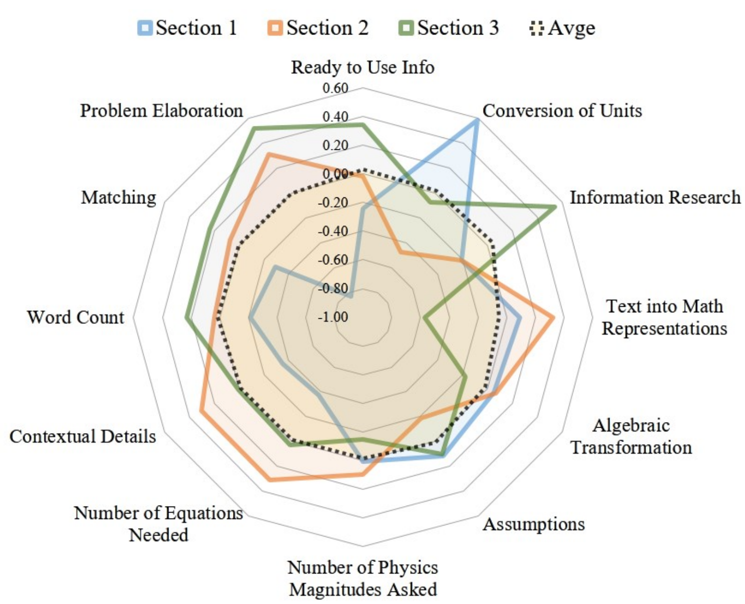

Figure 4.11: Average Problem Characteristics by Section.

The number of physics magnitudes is similar across sections and equivalent to the overall mean of the sample (Traditional = .1; Mixed = .01; Treatment = -.15). Yet, this is not reflected in the number of equations needed, with problem from Traditional section (.31) requiring more than the average number of math formulae for their solution, whereas activities from Mixed section (-.36) need less than the sample mean. Similar situation is observed form contextual details, with Traditional (.3) adding more contextual details than the average. In terms of word count, matching and sum, it is Treatment section (.23; .23; .67 respectively) the one that scores above the mean. The average score for variable Problem Elaboration would suggest the relative quality and complexity of the problems created by each section. Accordingly, learning activities generated in Mixed section (-.73) are the least elaborated, while problems from Traditional and Treatment classrooms showed a score of .44 and .67 respectively.

4.3 Social Network Analysis

This section shows the results of the social network analysis conducted for students' performance in physics test and problem elaboration. Results are presented as follow: First, I show whether differences exist across sections on the mentioned performance variables through analysis of variance (ANOVA). Second, I proceed to explore structural characteristics across sections, by using regression models with network variables (i.e., centrality, density and brokerage measures) as dependent variables. The third section aims to show the predictive value of network variables over physics grades, and to explore whether the network effects are invariant to sections and their respective instruction strategy. Similarly, I then explore whether network variables enable good performance at designing physics problems, and whether these effects are similar/different depending on the section. The final part of this results explores the existence of a moderating effect of network variables for the relationship between problem elaboration and physics grades. The latter analysis was conducted following the logic that students who created good problems (i.e., high problem elaboration) by obtaining ideas and other from their peers (i.e., high social interaction) may gain access to quality information, and as consequence, are likely to get good grades.

Sample statistics for the variables used in this study, including control variables are presented in Table 4.5. For testing the models, all independent variables were standardized (i.e., mean = 0; s.d = 1).

Table 4.5: Descriptive Statistics

Variable Names	Mean	St. Deviation	Valid N
1. Physics Grades	4.05	1.41	67
2. Problem Elaboration	-0.22	3.75	65
3. Indegree Centrality	4.12	2.21	67
4. Outdegree centrality	4.15	5.12	67
5. Log(Degree)	1.84	0.52	67
6. Log(Betweenness)	1.23	1.31	67
7. Eigenvector Centrality	0.39	0.30	67
8. Density	0.70	0.26	67
9. Constraint	0.60	0.27	67
10. Structural Holes	30.00	104.57	67
11. Coordinator	0.12	0.37	67
12. Gatekeeper	1.40	2.15	67
13. Representative	1.85	4.65	67
14. Liaison	1.54	4.57	67
15. University Selection Test (UST)	652.41	36.87	67
16. Section (Traditional =1; Mixed =2; Treatment = 3)	1.76	0.82	67
17. Engineer Major (Software Eng. = 1; Civil Eng. = 2)	1.67	0.47	67
18. Female	0.33	0.47	67
19. Good Student	8.24	3.82	67

4.3.1 Comparing Academic Performance across Sections

This section of analysis was conducted to explore the emergence of differences across sections on physics grades and problem elaboration. Figure 4.12 depicts physics grades and problem elaboration scores on each section. According to the scatter plots, students from the Mixed sections performed relatively worse than sections Traditional and Treatment on both outcome variables (Grades: M = 3.868, SD = 1.433; Problem Elaboration: M =-1.029, SD = 4.709). On physics grades, Traditional has a mean of M = 4.043 (SD = 1.442), while the Treatment section shows a mean score of M = 4.281 (SD = 1.353). On the variable problem elaboration their means are M = 0.133 (SD = 3.098), and M = 0.025 (SD = 3.529) respectively. The distribution of responses for physics grades looks similar for the three sections, as in consequence with the standard deviation, however, this is not the case for problem elaboration, where scores covered a wider range on mixed and treatment sections compared to traditional. The differences between the means of problem elaboration observed in here versus the one shown in problem description (page 138), are consequence of removing missing data for conducting this analysis.

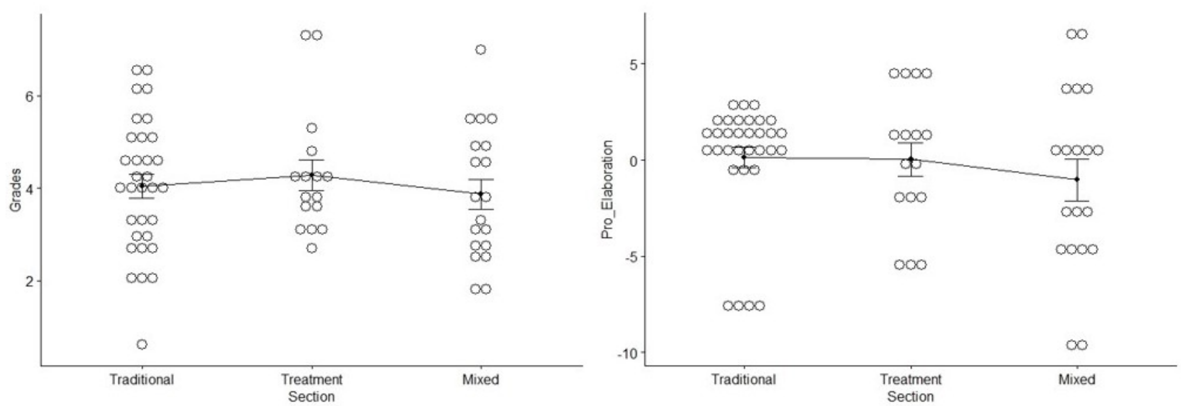

Figure 4.12: Scatter-plot of physics grades (left) and problem elaboration (right) for sections Traditional, Treatment and Mixed, with line connecting group mean.

At first glance, it seems that the mean differences on both variables are marginal across section. To explore whether these differences are significant I conducted analysis of variance on the outcome variables of interest. Levene's test for homogeneity of variance yields statistically non-significant for physics grades (p = 0.616), but significant for problem elaboration ($p = 0.04$), therefore the assumption of homogeneity of variance holds for the physics grades. The analysis of variance led to non-significant differences across sections for physics grades $F(2, 64) = 0.368$, $p = 0.693$, with similar non-significant results for problem elaboration ($F(2, 62) = 0.629$, $p = 0.536$). The latter evidence points out that the three sections did perform similarly when solving the textbooks physics problems designed for the test, as well as the elaboration of the problems designed as part of the ill-structured activity introduced the day of data collection. It is worth noticing that the analysis of variance was performed without taking into account the confounding (i.e., control) variables used on the following segments of analysis.

4.3.2 Section Comparison

As part of the descriptive exploration, in this section I analyzed the differences and similarities of the network variables computed for this study. The goal was to understand whether the social systems on each section reflected the same structures as a proxy of social activity. It is important to remember that the nature of the network emerged from the need to seek information for problem solving. This analysis was conducted for network predictors such as centrality measures, density and constraint, utilized as dependent variables in OLS multiple regression models. By including relevant confounding variables, this statistical technique enables a clear interpretation of the network activity on each section.

Comparing Network Centrality

Tables 4.6 and 4.7 (Regression for Centrality Network Variables) show the multiple regression coefficients for log(betweenness), indegree and outdegree centrality (Table 4.6), and for log(degree) and eigenvector (4.7). The key predictors for these models are

Mixed and Treatment section, whith Traditional acting as the baseline category. This means that the regression coefficient shown for Mixed, for instance, comes from the difference between Mixed and Traditional. The same interpretation holds for Treatment, private and charter schools, with public school being the baseline category.

Table 4.6: OSL multiple regression models for network centrality measures: Betweenness, Indegree and Outdegree.

	Dependent variable:			
	Log(Betweenness)	Indegree		Outdegree
	(1)	(2)	(3)	(4)
Mixed	−0.016	0.322	−0.666**	−0.540
	(0.419)	(0.293)	(0.282)	(0.411)
Treatment	0.225	0.412	0.177	−0.059
	(0.375)	(0.262)	(0.317)	(0.368)
UST	0.027	0.073	0.258*	0.118
	(0.173)	(0.121)	(0.142)	(0.169)
Same City	−0.275	0.008	0.067	−0.057
	(0.315)	(0.220)	(0.269)	(0.309)
Good Student	0.123	0.772***		−0.065
	(0.202)	(0.141)		(0.198)
Civil Eng.	0.018	0.061	0.400	−0.195
	(0.334)	(0.234)	(0.276)	(0.328)
Female	−0.217	0.179	−0.148	−0.148
	(0.307)	(0.215)	(0.252)	(0.301)
Private School	0.637	−0.035	0.381	0.582
	(0.520)	(0.364)	(0.435)	(0.511)
Charter School	0.266	0.132	0.251	−0.234
	(0.363)	(0.254)	(0.310)	(0.357)
Constant	−0.041	−0.389	−0.348	0.500
	(0.401)	(0.280)	(0.343)	(0.394)
Observations	67	67	67	67
R^2/Adjusted R^2	0.093/−0.051	0.556/0.486	0.324/0.231	0.126/−0.012
R. Std. Error	1.025 (df = 57)	0.717 (df = 57)	0.877 (df = 58)	1.006 (df = 57)
F Statistic	0.646 (df = 9; 57)	7.946*** (df = 9; 57)	3.477*** (df = 8; 58)	0.916 (df = 9; 57)
Note:				*p<0.1; **p<0.05; ***p<0.01

Model 1 indicates no difference in betweenness centrality among the three sections, therefore the level of overall connectivity measured with this metric is similar across sections, and with little explained variance. Models 2 and 3 for indegree centrality explain 55.6% and 32.4% of the variance observed in the sample. On model 2 there are no statistical differences between sections, with good student nomination being the only significant predictor for having high number of incoming ties in the network of information seeking. The logic behind this relationship is supported by the high correlation between indegree centrality and good student nomination ($r = 0.72$, $p < .05$), that is, being perceived as a skillful student in physics problem solving relates to the number individuals in the classroom that would direct their attention to seeking out information from perceived good students. When removing the predictor of good student nomination on model 3, the variance explained dropped more than 20%, while the significance was translated to Mixed section, and in a lesser degree to university selection test (UTS). Accordingly, the negative beta coefficient for Mixed section (i.e., difference between Mixed and Traditional) indicates that students from Traditional section were more active in being sought out for information from different peers compared to students in the Mixed section. Social activity here regards to receiving social ties form a variaty of other individuals, rather than intense interactions from a few. Further, the degree of social activity is similar for Traditional and Treatment, whereas having high scores in university selection test (UTS) serves as a partial indicator of good student nomination in predicting indegree centrality.

The differences observed in models for indegree are not replicated for predicting outdegree centrality (model 4). Let us remember that outdegree indicates the number of outgoing ties in the network of information seeking. Accordingly, the number of outgoing ties is similar between Treatment and Traditional. The negative effect over Mixed section aligns with the direction of the significant coefficient for indegree centrality (model 3), as students from Traditional section showed more social activity in seeking out information from a variety of individuals within the classroom, thus enabling others to increase their indegree scores. In addition, the null effect of good student nomination for outdegree might indicate that seeking out information is a social process engaged by students who enjoy different levels of 'academic prestige'.

Table 4.7: OSL multiple regression models for network centrality measures: Degree and Eigenvector.

	Dependent variable:		
	Log(Degree)		Eigenvector
	(1)	(2)	(3)
Mixed	-0.584^{*}	-0.965^{***}	0.211
	(0.332)	(0.266)	(0.367)
Treatment	0.261	0.170	0.694^{**}
	(0.297)	(0.299)	(0.329)
UST	0.140	0.211	0.025
	(0.137)	(0.134)	(0.151)
Same City	−0.129	−0.106	0.195
	(0.249)	(0.254)	(0.276)
Good Student	0.297^{*}		0.271
	(0.160)		(0.177)
Civil Eng.	0.147	0.277	0.573^{*}
	(0.265)	(0.260)	(0.293)
Female	−0.079	−0.205	−0.030
	(0.243)	(0.238)	(0.269)
Private School	0.341	0.502	−0.116
	(0.412)	(0.411)	(0.456)
Charter School	−0.119	−0.073	-0.538^{*}
	(0.288)	(0.293)	(0.318)
Constant	0.180	0.196	−0.343
	(0.318)	(0.324)	(0.351)
Observations	67	67	67
R^2/Adjusted R^2	0.431/0.341	0.396/ 0.313	0.304/0.194
R. Std. Error	0.812 (df = 57)	0.829 (df = 58)	0.898 (df = 57)
F Statistic	4.794^{***} (df = 9; 57)	4.761^{***} (df = 8; 58)	2.761^{***} (df = 9; 57)
Note:			*p<0.1; **p<0.05; ***p<0.01

On Table 4.7, coefficients on models 1 and 2 for log(degree) would hold similar interpretation than the ones made for indegree and outdegree centrality, but masked under the total number of social ties rather than the direction of these. In this case, the differences among Traditional and Mixed section are the same, as well as the null diffence between Traditional and Treatment. Further, the effect of good student nomination is positive and significant to an alpha level of 0.1, thus suggesting a higher tendency for students who are perceived as proficient in physics to have higher number of social ties in the network. When removing the variable of perceived good student as a predictor for log(degree), the differences for Treatment and Mixed sections become more negative and significant at a 0.01 level.

The final centrality measure used as dependent variable is eigenvector centrality (model 3), a metric often associated with social prestige, as this network variable accounts for how well connected are the individuals with whom the focal actor shows ties with. Model 3 on Table 4.7 explains 30.4% of the variance, with Treatment showing a significant difference from Traditional, meaning that students in the former may enjoy higher social prestige as a measure of having ties with others who are well-connected (central). The next variable that depicts some significance is civil engineer at 0.1 level, indicating that compared to students from software engineer, these show higher eigenvector centrality. An interesting result comes from charter schools with a negative coefficient. Although one may expect bigger differences between students from private and public schools in this variable associated with social prestige, this difference emerged between charter and public high schools. One explanation for this may be that the majority of students that participate in the study graduated from a charter school (75%), compared to public (15%) and private (10%), and therefore, due to similarities in school experience, this group is likely to develop social ties among each other (i.e., homophily).

Comparing Network Density and Brokerage

Similarly, Tables 4.8 and 4.9 (Regression for Cohesion and Brokerage Varaibles) shows regression models for network density, constraint and structural holes (4.8). Network constrain is a metric defined as an inverse measure of social capital, while structural holes refers to whether a node connects two or more sections of the network that otherwise will be unconnected (i.e., brokerage). Moreover, on Table 4.9 I show the analysis for brokerage variables. As mentioned, brokerage is observed when an actor within the network acts as bridge between two not connected individuals, enabling information flow. The definitions used here account for whether the source and destination student belong to the same or different groups.

According to the first two models (density and network constraint), there are no significant differences across sections when it comes to network density and constraint. Consequently, a similar result is observed for structural holes, which suggest that students' networks across all three sections show similar access to unconnected portions of the classroom from where non-redundant information would flow.

Moreover, on model 1 (Table 4.9) for coordinator brokerage, one can see significant regression coefficients for UST, engineering major (civil engineering) and private school, yet, no statistical significance for Mixed and Treatment sections compared to Traditional. Because coordinator refers to connecting actors within groups, a particular social activity that is being engaged significantly more by students with high UST. Interestingly, gatekeeper brokerage is significantly higher for Mixed and Treatment, indicating that students on these section engaged significantly higher on the process of seeking out information to individuals from other groups. Even though it was mentioned that students from Mixed engaged in lower levels of social activity due to the negative and significant differences with Traditional section on degree centrality de-

Table 4.8: OSL multiple regression models for network Density, Cohesion and Structural Holes.

	Dependent variable:		
	Density (1)	Constraint (2)	Structural Holes (3)
Mixed	0.266	0.278	−0.632
	(0.418)	(0.378)	(0.407)
Treatment	0.183	−0.173	−0.322
	(0.374)	(0.339)	(0.364)
UST	0.097	−0.088	0.002
	(0.172)	(0.156)	(0.168)
Same City	0.358	0.162	−0.149
	(0.314)	(0.285)	(0.306)
Good Student	0.165	−0.233	−0.092
	(0.202)	(0.183)	(0.196)
Civil Eng.	−0.274	−0.152	−0.041
	(0.333)	(0.302)	(0.324)
Female	0.449	0.317	−0.241
	(0.306)	(0.277)	(0.298)
Private School	−0.727	−0.595	0.266
	(0.519)	(0.470)	(0.505)
Charter School	−0.504	−0.427	−0.508
	(0.363)	(0.328)	(0.353)
Constant	0.089	0.211	0.820^{**}
	(0.400)	(0.362)	(0.390)
Observations	67	67	67
R^2/Adjusted R^2	0.096/−0.046	0.259/0.142	0.144/0.009
R. Std. Error (df = 57)	1.023	0.926	0.995
F Statistic (df = 9; 57)	0.675	2.215^{**}	1.067
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4.9: OSL multiple regression models for brokerage definitions: Coordinator, Gatekeeper, Representative and Liaison.

	Dependent variable:			
	Coordinator	Gatekeeper	Representative	Liaison
	(1)	(2)	(3)	(4)
Mixed	−0.154	0.806**	−0.659	−0.199
	(0.382)	(0.349)	(0.406)	(0.390)
Treatment	0.031	0.714**	−0.187	−0.192
	(0.342)	(0.313)	(0.364)	(0.350)
UST	0.396**	0.065	−0.016	−0.122
	(0.157)	(0.144)	(0.167)	(0.161)
Same City	0.291	−0.321	−0.347	0.140
	(0.287)	(0.263)	(0.306)	(0.294)
Good Student	−0.011	0.682***	−0.156	0.187
	(0.184)	(0.169)	(0.196)	(0.188)
Civil Eng.	−0.624**	−0.051	0.110	0.168
	(0.305)	(0.279)	(0.324)	(0.311)
Female	0.095	0.168	−0.288	−0.229
	(0.280)	(0.256)	(0.298)	(0.286)
Private School	1.130**	0.473	0.373	1.012**
	(0.474)	(0.434)	(0.505)	(0.485)
Charter School	0.247	0.414	−0.371	−0.115
	(0.331)	(0.303)	(0.353)	(0.339)
Constant	−0.096	−0.528	0.749*	−0.064
	(0.366)	(0.335)	(0.389)	(0.374)
Observations	67	67	67	67
R^2/Adjusted R^2	0.246/0.127	0.369/0.269	0.146/0.011	0.212/0.087
R. Std. Error (df = 57)	0.934	0.855	0.994	0.955
F Statistic (df = 9; 57)	2.065**	3.701***	1.083	1.702
Note:				*p<0.1; **p<0.05; ***p<0.01

picted on Table 4.6, these results account for the social activity for information seeking removing student's groups. Finally, for brokerage representative and liaison, regression coefficients show no statistical differences across sections, thus suggesting similar levels of brokering interactions in which students sent out information from the group to the others (i.e., representative), and similarities in brokering information between two different groups (i.e., liaison).

4.3.3 Network Structures for Physics Grades

In this section I explore the network structures that predicted good academic results on physics grades. For this first wave of results, physics grades were regressed on centrality measures, network density, constraint, and brokerage variables controlling for the confounding variables described in the methods sections. The goal was to determine whether the mentioned network predictors would enable good results in a physics test designed by the three instructors responsible for teaching the course. Notice that, similar to the coefficients from Tables 4.6, 4.7 and 4.9, section coefficients were determined as the difference between the respective section and the baseline, here Traditional section. Finally, the interaction terms were introduced to investigate whether network structures facilitate performance and success differently across sections.

Table 4.10 summarizes the multiple regression models fitted using indegree centrality (1 & 2), outdegree centrality (3 & 4) and log(degree) (5 & 6). Notice that the second model for each predictor added the interaction with the section. Taking all the models, university selection test (UTS) was a positive and significant predictor of physics grades in the sample of students. Moreover, the regression coefficient for Treatment section was positive and significant at 0.1 and 0.05, with a large effect over grades. This result indicated that, after controlling for socio-demographic variables and UTS, students under the Treatment condition were likely to increase almost a point their grades, compared to what students in Traditional section would get under similar socio-demographic and UTS conditions. This result suggested important effects of the learning environment generated in Treatment section, and the teaching and learning methodology used to encourage good academic performance.

Table 4.10: OLS multiple regression models for Physics Grades on network centrality: Indegree; Outdegree: and Log(Degree).

	Dependent variable:					
	Physics Grades					
	(1)	(2)	(3)	(4)	(5)	(6)
Indegree	−0.185	−0.067				
	(0.248)	(0.303)				
Outdegree			-0.349^{**}	-0.337^{*}		
			(0.172)	(0.194)		
Log(Degree)					-0.529^{**}	-0.499^{*}
					(0.218)	(0.263)
UST	0.581^{**}	0.534^{**}	0.606^{***}	0.600^{**}	0.624^{***}	0.609^{**}
	(0.229)	(0.245)	(0.222)	(0.226)	(0.219)	(0.231)
Same City	0.284	0.240	0.255	0.276	0.167	0.147
	(0.419)	(0.433)	(0.407)	(0.416)	(0.403)	(0.415)
Good Student	0.490	0.510	0.325	0.335	0.505^{*}	0.502^{*}
	(0.327)	(0.333)	(0.257)	(0.264)	(0.261)	(0.267)
Civil Eng.	−0.233	−0.201	−0.316	−0.319	−0.186	−0.130
	(0.439)	(0.453)	(0.427)	(0.440)	(0.420)	(0.462)
Female	−0.476	−0.443	−0.555	−0.573	−0.517	−0.531
	(0.409)	(0.417)	(0.394)	(0.403)	(0.388)	(0.399)
Mixed Section	0.881	0.551	0.627	0.465	0.467	0.514
	(0.559)	(0.691)	(0.545)	(0.654)	(0.549)	(0.690)
Treatment	0.937^{*}	0.955^{*}	0.838^{*}	0.823^{*}	0.982^{**}	1.018^{**}
	(0.503)	(0.511)	(0.478)	(0.486)	(0.473)	(0.493)
Private School	0.226	0.193	0.447	0.490	0.493	0.511
	(0.693)	(0.703)	(0.681)	(0.704)	(0.671)	(0.687)
Charter School	0.128	0.028	0.030	0.095	0.094	0.111
	(0.485)	(0.503)	(0.470)	(0.507)	(0.462)	(0.473)
Problem Elaboration	0.038	−0.038	0.020	−0.011	−0.077	−0.077
	(0.177)	(0.198)	(0.172)	(0.187)	(0.176)	(0.201)
Indegree*Mixed		−0.603				
		(0.671)				
Indegree*Treatment		−0.162				
		(0.468)				
Outdegree*Mixed				−0.551		
				(1.181)		
Outdegree*Treatment				0.041		
				(0.506)		
Log(Degree)*Mixed						0.019
						(0.587)
Log(Degree)*Treatment						−0.174
						(0.538)
Log(Bet)*Mixed	3.557^{***}	3.617^{***}	3.804^{***}	3.744^{***}	3.731^{***}	3.695^{***}
	(0.535)	(0.545)	(0.517)	(0.554)	(0.504)	(0.531)
Observations	67	67	67	67	67	67
R^2/Adjusted R^2	0.238/0.085	0.249/0.065	0.284/0.140	0.287/0.112	0.305/0.165	0.306/0.136
R. Std. Error	1.344 (df = 55)	1.359 (df = 53)	1.303 (df = 55)	1.324 (df = 53)	1.284 (df = 55)	1.306 (df = 53)
F Statistic	1.560 (df = 11; 55)	1.354 (df = 13; 53)	1.980^{**} (df = 11; 55)	1.640 (df = 13; 53)	2.190^{**} (df = 11; 55)	1.799^{*} (df = 13; 53)
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Surprisingly, and contrary to results in the literature of social networks in education, centrality metrics showed a negative effect over physics grades. These effects were significant for outdegree and log(degree). Because outdegree refers to the number of outgoing ties, that is, the activity of seeking out information, one may interpret that students with high outdegree were less knowledgeable in physics, yet this process was engaged by students with diverse degrees of previous knowledge given the low and non-significant correlation with UST (r = .12, ns) and perceived as a good students in the classroom (r = .15, ns). Consequently, in the three sections, seeking out information to different peers was not a social process that enabled good results. Further, and even though non-significant, the negative coefficient for indegree centrality may suggest that having many actors requesting ideas for solving problems may hinder your chances for success. Most of the students with high indegree were also perceived as good students ($r = .72$, $p < .01$), and scored rather higher in the UST test ($r = .33$, $p < .01$). In general, having high number of social ties, either incoming or outgoing showed to be negatively related to physics grades, as seen on models 5 and 6 for log(degree).

To illustrate this evidence, figure 4.13 depicts classroom networks for information seeking. The network diagram informs outdegree centrality as the size of nodes, whereas color shades indicate the grade obtained in the physics test. In relation with the regression coefficients shown on model (2) for outdegree centrality, darker colors indicating good grades tend to be smaller (i.e., lower outdegree) and located at the periphery of the system. In contrast, higher outdegree shown in larger nodes displays light color, thus indicating lower physics grades.

Further, Table 4.11 shows similar analysis for log(betweenness) and eigenvector centrality. Model 1 for log(betweenness) yields a significant and negative regression coefficient for predicting grades. Betweenness centrality is often times understood as embeddedness in the network, as it measures the number of times a given node is in between

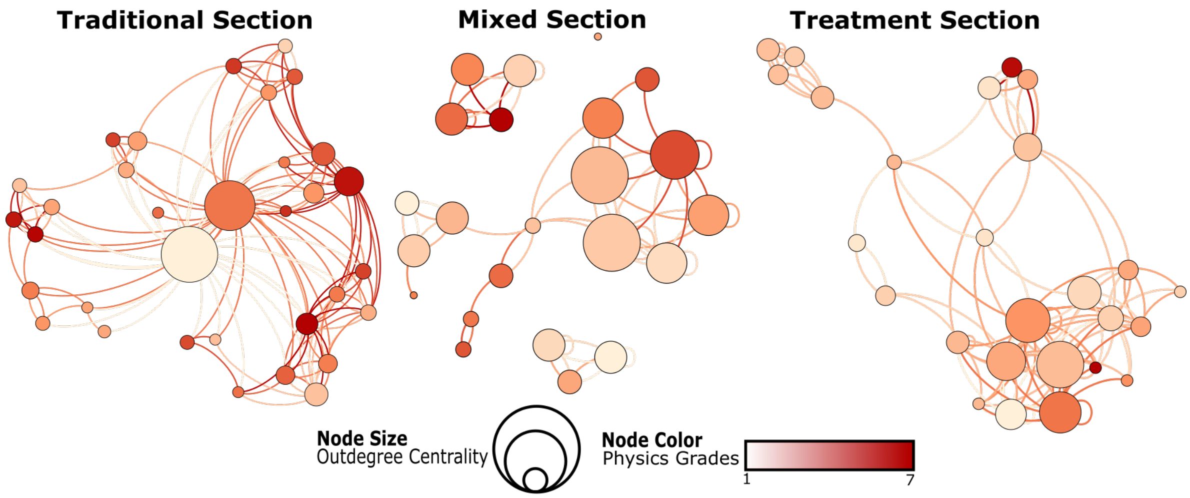

Figure 4.13: Classroom networks for sections Traditional, Mixed and Treatment.

the shortest path (i.e., geodesic distance) that connects two other nodes. Accordingly, socially active students with high betweenness would be the ones who enjoy some level of control over the information flowing throughout the network. The negative coefficient suggests that such control over the information did not afford academic success in well-structured problems. Moreover, the fact that log(betweenness) correlates weakly and insignificantly with good student nomination (r = .19, ns) and UST (r = .12, ns) would suggest that the students with diverse levels of academic prestige and prior knowledge enjoyed control over the information flowing throughout the network. Therefore, not taking advantage of this position was not an exclusive problem of students who lacked knowledge and social prestige.

For eigenvector centrality (model 3, Table 4.11), I observe a negative regression coefficient at 0.1 level of significance. High eigenvector centrality would enable access to multiple others who themselves are well-connected (i.e., central nodes). Again, this negative result would indicate that such privilege position within the network of information seeking is not rewarded by better grades. The interpretation of this coefficient is consistent with the latter results, as having numerous different social ties in the pursuit

Table 4.11: OSL multiple regression models for Physics Grades on network centrality: Log(Betweenness); and Eigenvector Centrality.

	Dependent variable:			
	Physics Grades			
	(1)	(2)	(3)	(4)
Log(Betweenness)	−0.331*	−0.428		
	(0.169)	(0.284)		
Eigenvector			−0.365*	−0.616
			(0.215)	(0.375)
UST	0.576**	0.597**	0.556**	0.591**
	(0.221)	(0.249)	(0.223)	(0.230)
Same City	0.190	0.193	0.298	0.265
	(0.410)	(0.430)	(0.411)	(0.416)
Good Student	0.388	0.399	0.446*	0.455*
	(0.258)	(0.278)	(0.266)	(0.268)
Civil Eng.	−0.239	−0.312	−0.058	−0.074
	(0.426)	(0.458)	(0.444)	(0.481)
Female	−0.580	−0.587	−0.480	−0.536
	(0.396)	(0.406)	(0.398)	(0.407)
Mixed Section	0.816	0.890	0.845	0.981*
	(0.538)	(0.573)	(0.542)	(0.561)
Treatment	0.936*	0.964*	1.095**	1.197**
	(0.480)	(0.490)	(0.501)	(0.518)
Private School	0.445	0.405	0.284	0.343
	(0.682)	(0.697)	(0.680)	(0.688)
Charter School	0.192	0.130	−0.030	−0.016
	(0.472)	(0.492)	(0.480)	(0.486)
Problem Elaboration	0.036	0.075	−0.097	−0.051
	(0.172)	(0.187)	(0.191)	(0.199)
Log(Betweenness)*Mixed		0.285		
		(0.507)		
Log(Betweenness)*Treatment		0.091		
		(0.441)		
Eigenvector*Mixed				0.459
				(0.457)
Eigenvector*Treatment				0.129
				(0.530)
Constant	3.615***	3.701***	3.511***	3.510***
	(0.511)	(0.541)	(0.520)	(0.531)
Observations	67	67	67	67
R^2/Adjusted R^2	0.281/0.137	0.285/0.109	0.269/0.122	0.286/0.110
R. Std. Error	1.306 (df = 55)	1.326 (df = 53)	1.316 (df = 55)	1.325 (df = 53)
F Statistic	1.950* (df = 11; 55)	1.624 (df = 13; 53)	1.836* (df = 11; 55)	1.630 (df = 13; 53)

Note: *p<0.1; **p<0.05; ***p<0.01

of information for solving physics problems is detrimental for academic success. We extend our interpretation of these results in the discussion section.

Finally, the interaction terms between section and the network predictors yield to no significant results on models from Tables 4.10 and 4.11, depicting little to no effect over the predictive value of the models, as the gains in variance explained are 2% in the best case (model 4 for eigenvector centrality). This provides evidence on the stable nature of the centrality measures used across the three sections, where social structures hold similar effects over performance in physics tests.

Following with the analysis, Table 4.12 shows the regression models for physics grades with network density, constraint and structural holes as the key predictors. Again, across all models, UTS emerged as a significant predictor of good grades, as well as Treatment section. Both network density and constraint are highly correlates predictors ($r = .73$, $p < .01$), and both set of models showed the same directionality in its relationships with physics grades. Network density indicates the percentage of social ties for a given actor in the network, relative to the total number of possible ties the actor will have in the case she/he is connected to every other node in the network. Model 1 shows no significant effect of network density over grades, however, when introducing the interaction between section and the predictor (model 2), the regression coefficient, even though it remains insignificant, it increases as well as the percentage of explained variance (ΔR^2 =4.7%). This change may suggest that the structural property of network density may facilitate good grades differently across sections.

Network constraint (model 3) measured the extent to which someone's social connections were connected to each other in a redundant way. That is, high constraint would suggest low access to structural holes and its consequent lack of inflow for novel information due to high redundancy of connections. Here, regression coefficient was positive, yet not statistically significant. The direction of the coefficient is of interest,

Table 4.12: OSL multiple regression models for Physics Grades on network measures: Density; Constraint; and Structural Holes.

	Dependent variable:					
	Physics Grades					
	(1)	(2)	(3)	(4)	(5)	(6)
Density	0.143	0.458				
	(0.174)	(0.317)				
Constraint			0.158	0.558*		
			(0.193)	(0.318)		
Structural Holes					−0.399**	−0.369**
					(0.172)	(0.174)
UST	0.554**	0.504**	0.580**	0.648**	0.573**	0.545**
	(0.228)	(0.232)	(0.228)	(0.243)	(0.219)	(0.220)
Same City	0.232	0.073	0.252	0.109	0.234	0.121
	(0.424)	(0.433)	(0.421)	(0.424)	(0.403)	(0.412)
Good Student	0.324	0.392	0.384	0.494*	0.311	0.341
	(0.266)	(0.268)	(0.269)	(0.267)	(0.255)	(0.256)
Civil Eng.	−0.205	−0.193	−0.223	−0.196	−0.257	−0.114
	(0.441)	(0.439)	(0.439)	(0.462)	(0.421)	(0.435)
Female	−0.574	−0.468	−0.556	−0.475	−0.613	−0.633
	(0.413)	(0.413)	(0.409)	(0.401)	(0.392)	(0.395)
Mixed Section	0.785	0.860	0.773	1.185**	0.580	0.153
	(0.555)	(0.549)	(0.556)	(0.574)	(0.541)	(1.799)
Treatment	0.836*	0.914*	0.887*	1.069**	0.737	0.575
	(0.493)	(0.488)	(0.493)	(0.490)	(0.475)	(0.491)
Private School	0.334	0.304	0.335	0.332	0.320	0.456
	(0.704)	(0.694)	(0.704)	(0.688)	(0.666)	(0.678)
Charter School	0.174	−0.023	0.177	0.094	−0.112	−0.021
	(0.491)	(0.496)	(0.492)	(0.482)	(0.473)	(0.485)
Problem Elaboration	0.041	0.027	0.025	0.029	0.064	0.030
	(0.176)	(0.174)	(0.178)	(0.175)	(0.170)	(0.185)
Density*Mixed		−0.637				
		(0.398)				
Density*Treatment		0.087				
		(0.514)				
Constraint*Mixed				−0.851*		
				(0.426)		
Constraint*Treatment				−0.047		
				(0.553)		
Structural Holes*Mixed						−1.928
						(6.668)
Structural Holes*Treatment						−2.111
						(1.557)
Constant	3.616***	3.818***	3.596***	3.701***	3.955***	3.854***
	(0.526)	(0.529)	(0.527)	(0.521)	(0.524)	(0.540)
Observations	67	67	67	67	67	67
R^2/Adjusted R^2	0.240/0.087	0.289/0.114	0.239/0.087	0.303/0.132	0.299/0.159	0.323/0.157
R. Std. Error	1.342 (df = 55)	1.323 (df = 53)	1.342 (df = 55)	1.309 (df = 53)	1.289 (df = 55)	1.290 (df = 53)
F Statistic	1.575 (df = 11; 55)	1.654* (df = 13; 53)	1.574 (df = 11; 55)	1.772* (df = 13; 53)	2.134** (df = 11; 55)	1.946** (df = 13; 53)

Note: *p<0.1; **p<0.05; ***p<0.01

as this would support the evidence found by Rhee and Leonardi (2003) in regards to interrogation logic, and the fact that more redundant social ties would enable success on tasks grounded on well-bounded bodies of knowledge, such as algebra-based physics problems. Moreover, when introducing the interaction between sections and constraint (model 4), the regression coefficient increases its value and reaches significance at .1 level. The significant interaction emerges between Traditional and Mixed sections, with a negative coefficient, thus indicating that the relationship between grades and network constraint is more positive in the Traditional and Treatment classroom compared to its effect in the Mixed section.

To disentangle this relationship, Fig **??** shows the interaction between network constraint and sections in predicting physics grades. According to the plot, both Traditional (red) and Treatment section (green) show positive and rather similar slopes, whereas the effect of network constraint is negative for the Mixed section. In both classrooms (Traditional and Treatment), less access to structural holes (i.e., high constraint) is likely to afford good grades, whereas, low constraint is a positive predictor of grades only for the Mixed section. Because high constraint relates to low access to structural holes, the evidence found on Traditional and Treatment is consistent with the significant and negative regression coefficients found on models 5 and 6 for structural holes (Table 4.12. Both contrasting evidence have been found to be related to different social processes for learning, with idea recombination (Burt, 2004; Borgatti and Cross, 2003; Reagans and McEvily, 2003) benefiting from low constraint, while interrogation logic (Rhee and Leonardi, 2003) being possible on highly constrained social systems.

To interpret what it means for network constraint to predict physics grades, one must consider the nature of the social network measured, the type of information flowing though these ties, and more importantly, the features of the task. First, the test given to students reflected the content and information introduced into the social system, as a

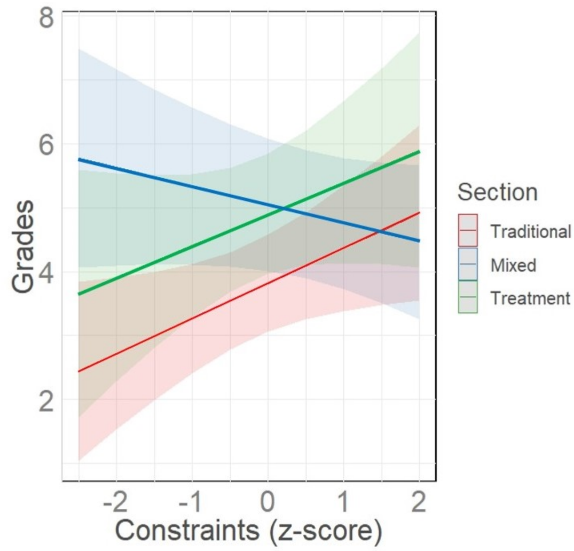

Figure 4.14: Interaction effect of Sections and network Constraint predicting Physics Grades.

common practice to assess the extent to which students were capable of utilizing physics concepts and principles for solving learning activities, such as math-based problems. The test and ultimately students' grades would illustrate the degree to which they were capable of manipulating a well bounded volume of information. Now, having high constraint in the network of information seeking implies that the targeted others were themselves connected to each other through incoming and/or outgoing ties, thus generating a dense network of peers through which the redundant content would flow. Moreover, and because the volume of knowledge needed for success in the test is well-defined and established, student might have enjoyed the benefits of reflecting upon the content with others within a cohesive network without experiencing the need of brokerage for creative combination (e.g., negative coefficient on gatekeeper brokerage on Table 4.13). According to the coefficient, being immerse in such a highly knitted network with no structural bridges connecting other partitions of the network would afford good grades.

Finally, table 4.13 summarizes the multiple regression models using brokerage vari-

Table 4.13: OSL multiple regression models for Physics Grades on network brokerage measures: Coordinator; Gatekeeper; Representative; and Liaison.

	Dependent variable:				
	Physics Grades				
	(1)	(2)	(3)	(4)	(5)
Coordinator	−0.013				
	(0.216)				
Gatekeeper		-0.396^{*}	−0.149		
		(0.203)	(0.399)		
Representative				-0.333^{*}	
				(0.195)	
Liaison					−0.007
					(0.197)
UST	0.851	1.150^{**}	0.862	0.753	0.764
	(0.582)	(0.563)	(0.654)	(0.647)	(0.762)
Same City	0.823	1.148^{**}	1.062^{**}	0.801	0.872^{*}
	(0.519)	(0.500)	(0.515)	(0.490)	(0.504)
Good Student	0.567^{**}	0.597^{***}	0.535^{**}	0.561^{**}	0.541^{**}
	(0.252)	(0.222)	(0.240)	(0.236)	(0.236)
Civil Eng.	0.288	0.165	0.062	0.169	0.244
	(0.433)	(0.412)	(0.438)	(0.428)	(0.434)
Female	0.350	0.617^{**}	0.584^{*}	0.303	0.379
	(0.271)	(0.292)	(0.299)	(0.270)	(0.276)
Mixed Section	−0.243	−0.261	−0.178	−0.231	−0.192
	(0.470)	(0.427)	(0.449)	(0.441)	(0.457)
Treatment	−0.532	−0.449	−0.530	−0.621	−0.516
	(0.422)	(0.396)	(0.414)	(0.411)	(0.418)
Private School	0.242	0.404	0.488	0.350	0.329
	(0.792)	(0.680)	(0.695)	(0.702)	(0.739)
Charter School	0.095	0.256	0.294	−0.047	0.122
	(0.498)	(0.477)	(0.490)	(0.492)	(0.499)
Problem Elaboration	0.042	0.061	−0.048	0.080	0.020
	(0.184)	(0.172)	(0.212)	(0.181)	(0.199)
Coordinant*Mixed	0.166				
	(0.619)				
Coordinant*Treatment	−0.188				
	(0.620)				
Gatekeeper*Mixed			−0.802		
			(0.889)		
Gatekeeper*Treatment			−0.270		
			(0.446)		
Representative*Mixed				0.480	
				(1.190)	
Representative*Treatment				−0.023	
				(0.542)	
Liaison*Mixed					−0.330
					(2.099)
Liaison*Treatment					−0.383
					(0.569)
Constant	3.638^{***}	3.418^{***}	3.480^{***}	3.911^{***}	3.597^{***}
	(0.544)	(0.522)	(0.544)	(0.552)	(0.541)
Observations	67	67	67	67	67
R^2/Adjusted R^2	0.234/0.046	0.280/0.136	0.291/0.118	0.276/0.098	0.238/0.051
Residual Std. Error	1.373 (df = 53)	1.306 (df = 55)	1.320 (df = 53)	1.334 (df = 53)	1.369 (df = 53)
F Statistic	1.242 (df = 13; 53)	1.945^{*} (df = 11; 55)	1.677^{*} (df = 13; 53)	1.553 (df = 13; 53)	1.270 (df = 13; 53)

Note: *p<0.1; **p<0.05; ***p<0.01

ables as predictors. Again, across all models being perceived as a good student emerged as a significant predictor of physics grades, while UST achieved some significance, replicating results from previous models. From model 1 for coordinator (i.e., students who mediate information between two actors from the same group who are not connected to each other), there were no significant effects over physics grades. Similar results were observed on model 5 for liaison, or brokering information on students from different groups. Gatekeeper brokerage, or accessing information from others outside one's group and bringing it to the team, showed a significant negative effect at 0.1 level on model 2. Interestingly, this type of brokerage is engaged by students with high indegree ($r = .73$, $p < .01$) and good students ($r = .5$, $p < .01$), being this variable characterized by good physics grades. This evidence may suggest that good students, or the ones with high indegree would perform worse if they focused on seeking out information outside their own groups. Further, representative brokerage, or mediating information from an actor in the same group to someone on a different group shows to have a negative effect over physics grades at 0.1 level. This is not a surprise given that this type of brokerage was engaged by students with high outdegree ($r = .89$, $p < .01$). Finally, these effects show to be stable across sections given the insignificant regression coefficients obtained after interacting section with these brokerage measures.

4.3.4 Network Structure for Problem Elaboration

For this result segment I conduced a similar set of multiple regression models to predict problem elaboration, a variable that accounts for the different set of characteristics identified in the sample of learning activities designed by student groups. Similarly from the models fitted for physics grades, independent predictors consisted of network centrality, cohesion and brokerage measures. In addition, these models included the interaction between the independent network predictors and section, in order to explore whether network variables enable success across sections.

Table 4.14 shows the coefficients of problem elaboration regressed on network centrality predictors. The first one should notice is the lack of significance, and in cases negative coefficient of UTS over problem elaboration. In contrast with physics grades, where this control variable showed a significant and positive effect. This contrasting evidence may be a consequence of the nature of the activities that led to both dependent variables, physics grades and problem elaboration. Whereas the former is grounded on solving well-defined physics problems, often associated with textbook and algebra-based problems, the latter is ill-structured, and thus demands decision making and a more creative mindset for generating solutions.

Models for indegree (1 & 2) and outdegree (3 & 4) show similar directions in the relations, and percentage of variance explained. On model 1, as well as for 3, there were no significant predictors for problem elaboration, with 12.3% and 12.6% of explained variance. When including the interaction between predictor and section, regression models for indegree (2) and outdegree (4) improved to explain 28.4% and 23.9% of the variance. This improvement leads to significant and negative coefficients for the Mixed section on models 2 and 4. These results indicate statistically significant differences between Treatment and Mixed sections on the relationship of indegree and outdegree for predicting problem elaboration. This interaction suggests the teaching and learning strategies enacted on Mixed and Traditional sections would lead to different effects for incoming and outgoing ties over problem elaboration. The changes in the regression coefficients for indegree and to a lesser level for outdegree, when introducing the interaction reflect the diverse effects of these network variables over performance on problem elaboration across sections, with contrasting relationships for the Mixed section compared to Treatment and Traditional classrooms. Finally, and because re-

Table 4.14: OLS multiple regression models for Problem Elaboration on network centrality measures: Indegree; Outdegree; and Log(Degree).

	Dependent variable:					
	Problem Elaboration					
	(1)	(2)	(3)	(4)	(5)	(6)
Indegree	−0.039	0.239				
	(0.188)	(0.206)				
Outdegree			−0.061	0.024		
			(0.134)	(0.141)		
Log(Degree)					-0.345^{**}	−0.014
					(0.159)	(0.178)
UST	−0.152	−0.232	−0.147	−0.158	−0.106	−0.185
	(0.172)	(0.165)	(0.172)	(0.163)	(0.166)	(0.154)
Same City	−0.414	−0.437	−0.417	−0.288	−0.458	−0.425
	(0.312)	(0.292)	(0.312)	(0.300)	(0.301)	(0.275)
Good Student	−0.161	−0.061	−0.175	−0.134	−0.113	0.089
	(0.331)	(0.311)	(0.332)	(0.320)	(0.319)	(0.312)
Civil Eng.	0.031	0.071	−0.003	0.027	0.103	0.122
	(0.247)	(0.229)	(0.200)	(0.192)	(0.198)	(0.179)
Female	0.302	0.329	0.286	0.184	0.268	0.303
	(0.306)	(0.283)	(0.305)	(0.292)	(0.293)	(0.266)
Mixed Section	−0.386	-1.122^{**}	−0.432	-1.044^{**}	−0.600	-1.345^{***}
	(0.420)	(0.451)	(0.421)	(0.455)	(0.410)	(0.429)
Treatment	−0.131	−0.070	−0.151	−0.191	−0.057	0.044
	(0.380)	(0.352)	(0.371)	(0.353)	(0.360)	(0.334)
Private School	0.695	0.485	0.731	0.845^{*}	0.814^{*}	0.780^{*}
	(0.516)	(0.480)	(0.521)	(0.500)	(0.499)	(0.453)
Charter School	0.477	0.153	0.457	0.693^{*}	0.430	0.398
	(0.361)	(0.346)	(0.361)	(0.357)	(0.347)	(0.315)
Indegree*Mixed		-1.451^{***}				
		(0.418)				
Indegree*Treatment		−0.347				
		(0.319)				
Outdegree*Mixed				-2.267^{***}		
				(0.803)		
Outdegree*Treatment				−0.051		
				(0.369)		
Log(Degree)*Mixed						-1.336^{***}
						(0.353)
Log(Degree)*Treatment						−0.504
						(0.357)
Constant	0.043	0.179	0.089	−0.208	0.121	−0.117
	(0.404)	(0.374)	(0.403)	(0.403)	(0.383)	(0.359)
Observations	67	67	67	67	67	67
R^2/Adjusted R^2	0.123/−0.033	0.284/0.125	0.126/−0.030	0.239/0.069	0.190/0.046	0.362/0.220
Residual Std. Error	1.016 (df = 56)	0.936 (df = 54)	1.015 (df = 56)	0.965 (df = 54)	0.977 (df = 56)	0.883 (df = 54)
F Statistic	0.788 (df = 10; 56)	1.783^{*} (df = 12; 54)	0.807 (df = 10; 56)	1.410 (df = 12; 54)	1.317 (df = 10; 56)	2.550^{***} (df = 12; 54)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

gression coefficients for Treatment section and its interactions are not significant on models 1-4, one may say that incoming ties for information seeking (indegree), as well as seeking out information to multiple others in the classroom (outdegree) show no differential effects over the elaboration of students' problems, in comparison with the Traditional section. The interactions of section and these centrality measures for predicting problem elaboration are shown on Figure 4.15 (A: ndegree; B: outdegree; C: log(degree); and D: log(betweenness)). According to Figure 4.15 A and B, it is possible to identify the drastic difference between Traditional (red) and Treatment (green) with Mixed (blue) sections over the effect of indegree and outdegree centrality for enabling good performance in problem elaboration, where having either incoming or outgoing ties for information seeking was positively related to problem elaboration on sections Traditional and Treatment.

Model 5 for log(degree) provides a negative and significant effect of degree centrality for problem elaboration. Moreover, and similar to models 2 and 4, when including the interaction between log(degree) and section on model 6, the percentage of variance explained improved from 19 % to 36.2% for problem elaboration, which brings significance to Mixed section as a single predictor, as well as its interaction. This interaction reduced the solo effect of log(degree) on problem elaboration, which is interpreted as a consequence of adding the structural relationships per section, where Mixed section has shown a more negative effect. In general, coefficients on model 6 hold the same interpretation than models 2 and 4, as the number of social ties does not indicate an effect over the dependent variable across the sample, but would yield to worse outcomes on students from the Mixed section, whereas this relation may not be as negative for students in Treatment and Traditional classrooms. The latter set of relationships is observed in Figure 4.15 C for log(degree).

Table 4.15 shows similar regression models for problem elaboration but using log(betweenness)

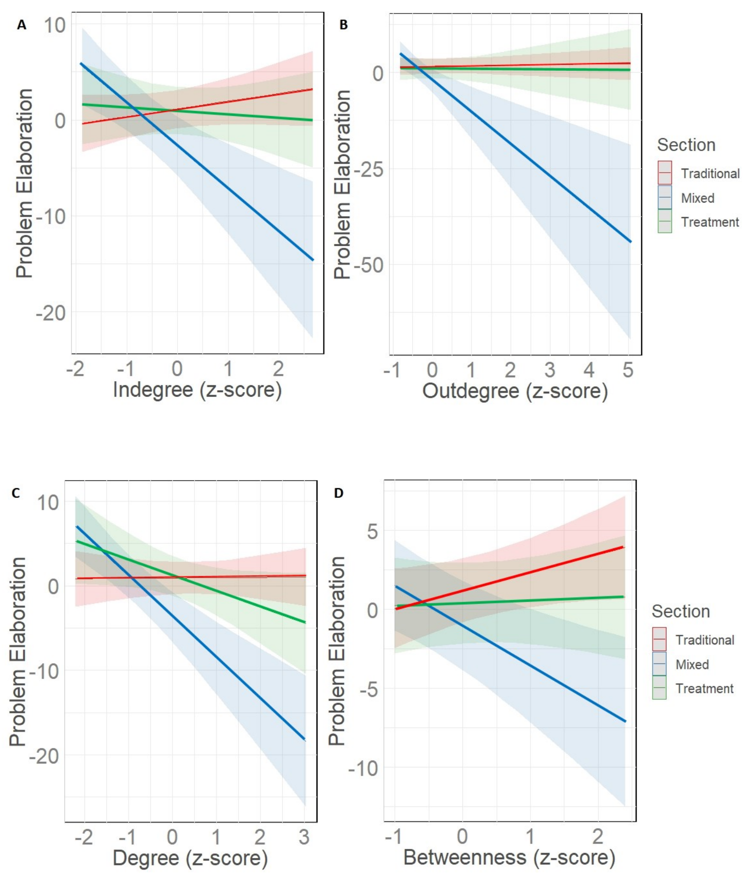

Figure 4.15: Interaction effect of Sections and Centrality measures predicting Problem Elaboration: A. Indegree; B. Outdegree; C. Log(Degree); and D. Log(Betwenness).

Table 4.15: OLS multiple regression models for Problem Elaboration on network centrality measures: Log(Betweenness); and Eigenvector centrality.

	Dependent variable:			
	Problem Elaboration			
	(1)	(2)	(3)	(4)
Log(Betweenness)	−0.017	0.302		
	(0.131)	(0.202)		
Eigenvector			-0.477^{***}	−0.058
			(0.136)	(0.257)
UST	−0.154	−0.193	−0.143	−0.193
	(0.171)	(0.179)	(0.155)	(0.155)
Same City	−0.418	−0.357	−0.321	−0.291
	(0.314)	(0.308)	(0.284)	(0.281)
Good Student	0.003	−0.048	0.130	0.101
	(0.201)	(0.202)	(0.185)	(0.183)
Civil Eng.	−0.163	0.103	0.110	0.253
	(0.331)	(0.332)	(0.310)	(0.327)
Female	0.291	0.267	0.281	0.277
	(0.306)	(0.293)	(0.276)	(0.276)
Mixed Section	−0.399	−0.618	−0.298	−0.433
	(0.415)	(0.408)	(0.377)	(0.379)
Treatment	−0.143	−0.226	0.184	0.134
	(0.373)	(0.355)	(0.350)	(0.354)
Private School	0.707	0.742	0.640	0.577
	(0.523)	(0.496)	(0.468)	(0.464)
Charter School	0.476	0.625^{*}	0.215	0.227
	(0.362)	(0.347)	(0.334)	(0.331)
Log(Betweenness)*Mixed		-0.988^{***}		
		(0.342)		
Log(Betweenness)*Treatment		−0.265		
		(0.318)		
Eigenvector*Mixed				-0.574^{*}
				(0.303)
Eigenvector*Treatment				−0.509
				(0.356)
Constant	0.058	−0.247	−0.105	−0.166
	(0.398)	(0.392)	(0.363)	(0.363)
Observations	67	67	67	67
R^2/Adjusted R^2	0.123/−0.034	0.242/0.073	0.281/0.153	0.327/0.178
Residual Std. Error	1.017 (df = 56)	0.963 (df = 54)	0.920 (df = 56)	0.907 (df = 54)
F Statistic	0.785 (df = 10; 56)	1.435 (df = 12; 54)	2.191^{**} (df = 10; 56)	2.191^{**} (df = 12; 54)
Note:				*p<0.1; **p<0.05; ***p<0.01

and eigenvector centrality as main predictors. From model 1 for betweenness centrality, one could say that being located within multiple shortest paths between two actors in the network of information seeking shows no effect over problem elaboration. Further, eigenvector centrality on model 3 showed to be negatively related to problem elaboration, that is, students who are linked to well-connected others in the network of information seeking do worse than those who do not enjoy such social prestige. Model 2 and 4 includes the interaction between section and betweenness (2) and eigenvector (4), and yields a negative effect of centrality on the Mixed section for betweenness and for eigenvector, when compared to Traditional section. Similarly to section interactions for indegree, outdegree and log(degree) in Table 4.14, including the interaction makes the centrality effect positive or less negative (close to zero), yet not significant. Again, Figure 4.15 D depicts the interaction between sections and log(betweenness) for predicting problem elaboration. Here, Mixed section (blue) displays a negative relationship for students highly embedded in the network of information seeking. In contrast, students from Traditional (red) and Treatment (green) benefit from this social structure.

In general, all three social systems (Traditional, Mixed and Treatment) enable academic success through different social processes, as being reflected by the regression models on Tables 4.14 and 4.15. Consistently across different network centrality measures, central students are not rewarded with good scores on problem elaboration, while these effects seemed to be less negative on the Treatment and Traditional sections.

Next, Table 4.16 summarizes the models for problem elaboration regressed on network density, constraint and structural holes. The first four models for network density and constraint with their respective interactions yield to no significant coefficients. Yet, one should notice that, compared to the regression coefficients from Table 4.8, the directions of these effects for grades tend to go in the opposite direction than for physics grades. Along with the lack of significance for UST on problem elaboration, this becomes interesting evidence to support the distinctive nature of designing problems when compared to well-structured activities.

Table 4.16: OSL multiple regression coefficients for Problem Elaboration on network measures: Density; Constraint; and Structural Holes.

	Dependent variable:					
	Problem Elaboration					
	(1)	(2)	(3)	(4)	(5)	(6)
Density	0.005 (0.132)	−0.027 (0.247)				
Constraint			0.124 (0.144)	−0.050 (0.247)		
Structural Holes					0.059 (0.135)	0.098 (0.127)
UST	−0.155 (0.172)	−0.178 (0.180)	−0.144 (0.171)	−0.223 (0.186)	−0.155 (0.171)	−0.130 (0.161)
Same City	−0.416 (0.316)	−0.462 (0.332)	−0.434 (0.311)	−0.494 (0.322)	−0.405 (0.313)	−0.380 (0.298)
Good Student	−0.000 (0.202)	0.023 (0.209)	0.030 (0.202)	0.022 (0.207)	0.006 (0.201)	−0.008 (0.188)
Civil Eng.	−0.162 (0.333)	−0.137 (0.343)	−0.144 (0.330)	0.013 (0.359)	−0.161 (0.331)	0.011 (0.320)
Female	0.293 (0.310)	0.320 (0.320)	0.256 (0.306)	0.248 (0.309)	0.309 (0.306)	0.338 (0.287)
Mixed Section	−0.400 (0.417)	−0.376 (0.426)	−0.433 (0.415)	−0.449 (0.442)	−0.362 (0.423)	-3.941^{***} (1.209)
Treatment	−0.148 (0.373)	−0.133 (0.380)	−0.126 (0.371)	−0.085 (0.380)	−0.128 (0.374)	−0.146 (0.360)
Private School	0.699 (0.525)	0.696 (0.534)	0.770 (0.520)	0.784 (0.523)	0.680 (0.517)	0.795 (0.487)
Charter School	0.474 (0.367)	0.458 (0.382)	0.524 (0.363)	0.535 (0.367)	0.501 (0.366)	0.633^{*} (0.346)
Density*Mixed		−0.007 (0.311)				
Density*Treatment		0.188 (0.401)				
Constraint*Mixed				0.179 (0.329)		
Constraint*Treatment				0.492 (0.424)		
Structural Holes*Mixed						-14.196^{***} (4.505)
Structural Holes*Treatment						−0.661 (1.141)
Constant	0.058 (0.398)	0.074 (0.413)	0.032 (0.397)	−0.036 (0.405)	0.011 (0.412)	−0.263 (0.396)
Observations	67	67	67	67	67	67
R^2/Adjusted R^2	0.123/−0.034	0.127/−0.066	0.134/−0.021	0.155/−0.033	0.126/−0.030	0.264/0.100
Residual Std. Error	1.017 (df = 56)	1.033 (df = 54)	1.010 (df = 56)	1.016 (df = 54)	1.015 (df = 56)	0.948 (df = 54)
F Statistic	0.784 (df = 10; 56)	0.658 (df = 12; 54)	0.867 (df = 10; 56)	0.826 (df = 12; 54)	0.805 (df = 10; 56)	1.614 (df = 12; 54)
Note:						*p<0.1; **p<0.05; ***p<0.01

The best predictive regression becomes model 6 for structural holes and its interaction with section as main predictors. Here, structural holes is an attributes associated with social capital, and indicates the number of unconnected individuals who have social ties with a common actor. Once again, the Mixed section showed lower performance on problem elaboration compared to the Traditional group, as well as a large negative interaction. Accordingly, having access to multiple structural holes, and the non-redundant information these may provide does not afford better solutions when it comes to problem design, relative to students under the Traditional condition, which themselves experience similar benefits than students from the Traditional group.

Finally, Table 4.17 depicts multiple regression models for problem elaboration using brokerage measures as main predictors, along with interaction with section. Model 1 for coordinator (i.e., mediating information between team-members who are not connected) shows no statistical significance even with the interaction with section. Gatekeeper brokerage shows to be statistically insignificant (model 2), yet, when including the interaction term with section (model 3), the variance explained improves from 12.6% to 41.2%, yielding a positive and significant coefficient for predicting problem elaboration above and beyond the differences associated with sections. In addition, the interaction term is negative for Mixed compared Traditional section and statistically significant at .05 level, and less negative for Treatment relative to Traditional, but at .01 level of significance. The main effect of gatekeeper brokerage suggest that students who bring information from other groups to share with members on their team are likely to get almost .6 more points in problem elaboration.

Figure 4.16 depicts the relationship between problem elaboration and gatekeeper by section. According to the plot, and similar to the interactions shown in previous models, Mixed section depicts a negative slope, while being a gatekeeper in Traditional and Treatment sections related to better problem elaboration. The change in predictive value and significance between models 3 and 4 is perceived as a consequence of accounting for differences between sections, thus 'cleaning' the effect for the main predictor over the dependent variable. These changes are observed in previous models, yet neither as high as this effect. Finally, models for representative and liaison show

Table 4.17: OSL multiple regression models for Problem Elaboration on network brokerage measures: Coordinator; Gatekeeper; Representative; and Liaison.

	Dependent variable:				
	Problem Elaboration				
	(1)	(2)	(3)	(4)	(5)
Coordinator	0.145				
	(0.159)				
Gatekeeper		0.067	0.597^{**}		
		(0.157)	(0.243)		
Representative				0.141	
				(0.145)	
Liaison					0.009
					(0.135)
UST	−0.492	−0.453	-1.175^{***}	−0.738	-1.395^{***}
	(0.426)	(0.434)	(0.389)	(0.475)	(0.487)
Same City	−0.241	−0.195	−0.359	−0.111	−0.132
	(0.383)	(0.388)	(0.327)	(0.368)	(0.345)
Good Student	−0.225	−0.159	−0.246	−0.150	−0.165
	(0.184)	(0.171)	(0.151)	(0.176)	(0.160)
Civil Eng.	−0.395	−0.392	-0.501^{*}	−0.349	−0.424
	(0.316)	(0.316)	(0.273)	(0.318)	(0.291)
Female	0.0002	−0.045	−0.107	0.012	0.094
	(0.201)	(0.227)	(0.191)	(0.203)	(0.189)
Mixed Section	−0.055	−0.160	0.070	−0.075	0.038
	(0.348)	(0.331)	(0.288)	(0.331)	(0.313)
Treatment	0.336	0.284	0.003	0.355	0.142
	(0.309)	(0.305)	(0.266)	(0.305)	(0.286)
Private School	0.895	0.664	0.717	0.618	0.602
	(0.574)	(0.521)	(0.435)	(0.520)	(0.500)
Charter School	0.412	0.443	0.456	0.553	0.538
	(0.364)	(0.366)	(0.308)	(0.362)	(0.334)
Coordinant*Mixed	−0.504				
	(0.454)				
Coordinant*Treatment	−0.473				
	(0.455)				
Gatekeeper*Mixed			-2.399^{***}		
			(0.469)		
Gatekeeper*Treatment			-0.537^{*}		
			(0.277)		
Representative*Mixed				-1.580^{*}	
				(0.867)	
Representative*Treatment				−0.120	
				(0.407)	
Liaison*Mixed					-4.416^{***}
					(1.307)
Liaison*Treatment					−0.238
					(0.389)
Constant	−0.014	0.094	0.160	−0.155	−0.110
	(0.403)	(0.406)	(0.349)	(0.414)	(0.371)
Observations	67	67	67	67	67
R^2/Adjusted R^2	0.154/−0.034	0.126/−0.031	0.412/0.281	0.178/−0.004	0.280/0.120
Residual Std. Error	1.017 (df = 54)	1.015 (df = 56)	0.848 (df = 54)	1.002 (df = 54)	0.938 (df = 54)
F Statistic	0.819 (df = 12; 54)	0.804 (df = 10; 56)	3.148^{***} (df = 12; 54)	0.978 (df = 12; 54)	1.749^{*} (df = 12; 54)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

no statistical significance over problem elaboration, yet, their interactions with section yield to negative and significant coefficients for Mixed section compared to Tradition classroom.

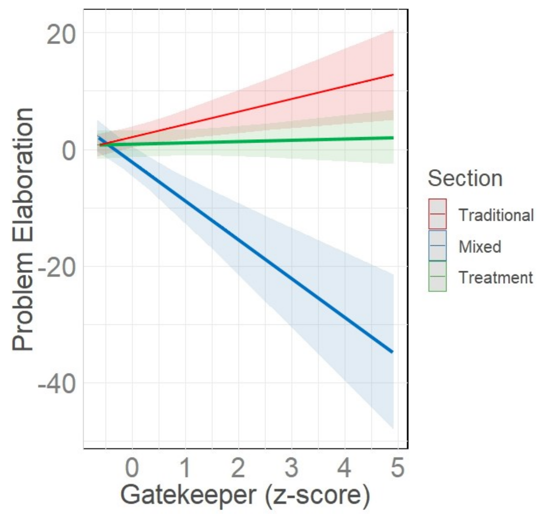

Figure 4.16: Interaction effect of Sections and network Constraint predicting Physics Grades.

4.3.5 Moderated Network effect of Problem Elaboration on Physics Grades.

In this final section of social network analysis, I tested the existence of a network variable moderating the relationship between problem elaboration and physics scores. Because having designed a physics problem has shown statistically insignificant coefficients in predicting physics grades (see Tables 4.10, 4.11, 4.12 and 4.13), I considered the possibility that the relationship between problem elaboration and physics grades to be moderated by students' networks. In performing this analysis I focused on significant network predictors of physics grades, and then test the interaction effect. Here I present multiple regression models that yielded significant results, with moderators in log(degree) and eigenvector centrality. Given that regression coefficients for network centrality such as log(degree) and eigenvector are negative, it may not be surprising to see that a negative interaction, thus suggesting that students with high network centrality and who scored high in problem elaboration may not necessarily benefit by getting good physics grades. In addition to network moderators, I tested the moderating effect of perceived good students over the relationship between problem elaboration and physics grades, by following the rationale that different levels of problem elaboration may have enabled differences in conceptual understanding and abilities for solving well-structured problems (i.e., physics grades), at different levels of perceived status (i.e., good students). With this, I explored whether the effect of problem elaboration over physics grades depends of perceived status as good students or is invariant to all participants.

Table 4.18 depicts the regression models for the moderator effect of log(degree), eigenvector and good students on the relationship between problem elaboration and physics grades. Again, single effect of problem elaboration was close to zero in predicting grades. According to model 1, log(degree) moderates the relationship between problem elaboration and physics grades. The same was observed on model 2 for the interaction between eigenvector and problem elaboration. Both interactions were negative, and consistent with the single effect of the network predictors over physics grades. The same directionality was observed on model 3, for good students.

To interpret the moderated effect of these variables, Figure 4.17 depicts the interactions at different levels of the moderator (M-1SD in red; M in blue; M+1SD in green). First, for log(degree) (Fig. 4.17 A), students who score low in problem elaboration and show low log(degree) centrality (red) would score lower physics grades than those who score low in problem elaboration, but show average (blue) and high (green) log(degree). In contrast, scoring high in problem elaboration reflects high physics grades

Table 4.18: OSL multiple regression models for moderating effect in predicting Physics Grades.

	Dependent variable:		
	Physics Grades		
	(1)	(2)	(3)
Log(Degree)	−0.431*		
	(0.216)		
Eigenvector		−0.403*	
		(0.210)	
Problem Elaboration	−0.103	−0.068	−0.020
	(0.170)	(0.187)	(0.172)
Good Student	0.507**	0.486*	0.425
	(0.253)	(0.260)	(0.257)
UST	0.595***	0.536**	0.593***
	(0.212)	(0.218)	(0.219)
Same City	−0.041	0.206	0.122
	(0.401)	(0.404)	(0.409)
Civil Eng.	−0.108	−0.123	−0.155
	(0.408)	(0.434)	(0.423)
Female	−0.576	−0.475	−0.577
	(0.376)	(0.389)	(0.391)
Mixed Section	0.407	0.548	0.948*
	(0.531)	(0.551)	(0.534)
Treatment	0.886*	0.991**	0.869*
	(0.460)	(0.492)	(0.473)
Private School	0.502	0.249	0.299
	(0.649)	(0.664)	(0.666)
Charter School	−0.046	−0.257	0.064
	(0.451)	(0.483)	(0.465)
Log(Degree)*Problem Elaboration	−0.385**		
	(0.175)		
Eigenvector*Problem Elaboration		−0.351*	
		(0.182)	
Good Student*Problem Elaboration			−0.400**
			(0.174)
Constant	3.939***	3.766***	3.708***
	(0.497)	(0.524)	(0.506)
Observations	67	67	67
R^2	0.362	0.316	0.298
Adjusted R^2	0.220	0.164	0.157
Residual Std. Error	1.241 (df = 54)	1.285 (df = 54)	1.290 (df = 55)
F Statistic	2.548*** (df = 12; 54)	2.077** (df = 12; 54)	2.121** (df = 11; 55)
Note:			*p<0.1; **p<0.05; ***p<0.01

only for those who engage in lower social interactions for information seeking (i.e., low log(degree)), while having average (blue) and high (green) log(degree) seems to be detrimental for obtaining good grades. In coherence with previous models, problem elaboration afford opportunities for obtaining good grades only for students who show below average degree centrality, which is consistent with the interpretation made previously over the nature of the task, and the well-defined nature of the physics content being addressed in the course.

According to the coefficient similarities observed in models 2 and 4, Figure 4.17 B and C depicts same set of slopes for students who are one standard deviation below the mean in eigenvector (red), the ones who show average eigenvector (blue), and one standard deviation above the mean in this centrality measure (green). Consequently, the benefits of engaging in creating a highly elaborated physics problem were observed only for students with below average eigenvector centrality.

Finally, the interaction between good students and problem elaboration in predicting good grades (Fig. 4.17 C) showed that students who were not perceived as good in physics (red) would benefit from creating well elaborated problems, as this process would enable them to get good grades. In contrary, 'good students' (green and blue) were better off creating simple problems.

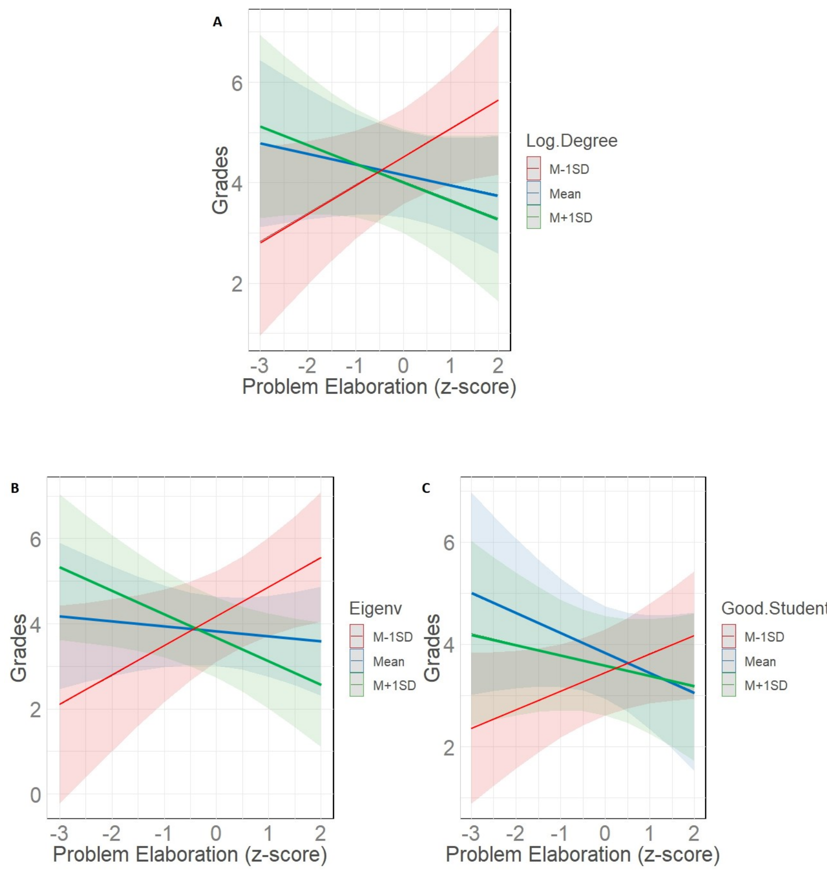

Figure 4.17: Interaction effect of Problem Elaboration and network centrality, and good student nomination for predicting Physics Grades: A. Problem Elaboration*Log(Degree); B. Problem Elaboration*Eigenvector; C. and Problem Elaboration*Good Student.

Chapter 5

Discussion and Conclusion

In this section, I discuss the results in the order in which these are shown in Chapter 4: 1. Group Processes and Discussion; 2 Problems' Description; and 3. Social Network Analysis. Results from these three categories provided interesting findings about how students engaged in generating problems, the nature of the ideas proposed for such purpose, and how the learning context influenced the ways in which they utilized physics concepts and other features into their solutions. Finally, the network dimension enabled a deeper understanding over the effect of social interactions for information seeking, as well as the different ways in which this social engagement enabled positive academic performance.

5.1 Group Processes and Discussion

Generating problems constitutes an authentic activity that the majority of educators must engage in, and, therefore is a real-world problem. Generating problems that require students to generate, apply and select subjective assumptions that would constrained the open-ended context into a well-defined one is complex (Fortus, 2008;

Rietman, 1964). The themes in the category of results, Decision Making, constituted the different dimensions that required subjective assumptions in order to solve the problem. These ideas include: 1. Learning goals; 2. Physics concepts and procedures; 3. Problem context and wording; 4. Magnitudes and units. The second category of results, Problem Solving Strategies, involves addressing 1. Algebraic procedures and 2. Physics of circular motion. According to Fortus's results (2009), assumptions regarding the physics variables and principles, and regarding the magnitudes of these variables are the two main assumptions necessary for solving ill-structured problems. The first assumption (i.e., physics variables and principles) is easier to make for novices (e.g., undergraduate physicists) and experts (e.g., graduate physicist), compared to assumptions regarding the numerical magnitudes of the variables used in the problem (Fortus, 2009). Using physics variables and principles are necessary for solving well-structured problems, and, as such, both groups of subjects presumably have experience in solving them. However, making assumptions about physics magnitudes is a skill that characterizes expert problem solvers, while novices struggle on this dimension (Fortus, 2009), likely because they lack experience in this area.

In connection with the themes from Decision Making, one may say that Physics Concepts and Procedures mirror the first type of physics assumption that is accessible to both novices and experts, whereas Magnitudes and Units might be consistent with the second type of assumption which is more familiar for experts. Extending the dichotomy in assumptions suggested in Fortus's work, I propose that assumptions about the Problem Context and Wording may be an alternative and more accessible assumption to make for both novices and experts, as both groups of students are likely to have experience reading different types of well-structured problems, with various contextual details and wording, and therefore may be more efficient in using that knowledge as resource for making their own assumptions. In contrast, and even though all participants have been exposed to learning activities of diverse nature, discussing and making decisions about the problems' Learning Goals may be more challenging, as this entails knowledge of the target students, which will ultimately mediate the problem's level of difficulty. The nature and demands over this type of assumption are presumably grounded on students' prior experience in high school. With this in mind, having students generate problems adds two alternative types of assumptions with arguably different levels of complexity for experienced and non-experienced solvers.

Developing the skills to make assumptions in both simple and complex dimensions may reflect Amabile's (1996) creative relevant skills and processes. From this perspective, one may perceive students' ideas and solutions from the lens of creativity, taking into account its two key characteristics, novelty and usefulness (Csikszentmihalyi, 2013; Runco and Jaeger, 2012; Sternberg, 2012). Beyond the possibility of understanding students' solutions from the perspective of creativity, one may also reflect on physics education as a creative learning environment supported by teaching strategies and assessments that encourage and reward good ideas, more than the reproduction of bottom-top strategies (Dufresne et al., 1992; Larkin et al., 1980).

In addition, results show that developing problems encouraged students to engage in both quantitative (Algebraic Procedures) and qualitative (Physics of Circular Motion) strategies for testing (solving) their problems, a recommended combination of strategies to overcome novices' superficial disposition to problem solving (Meltzer, 2005; Shing, 2008), and to foster top-down logic, that is, starting from general principles and then moving down to mathematical representations and equations (Dufresne et al., 1992; Larkin et al., 1980). It is important to notice the differences in time invested on these problem solving strategies, where students tended to favor algebraic procedures over qualitative descriptions. Reducing the gap between the time invested in algebraic procedures and qualitative descriptions of the content constitutes an additional challenge for physics educators, as shown in the literature (Byun and Lee, 2014), and further pedagogical innovation and research needs to be conducted on this matter. For instance, one may think about using characteristics from isomorphic sets of physics problems (Meltzer, 2005; Shing, 2008), in order to encourage students to generate problems with such characteristics (i.e., quantitative and conceptual problems around the same content). Here, generating both mathematical and conceptual problems on the same content may increase reflection over the content beyond the utilization of mathematical representations. In the likeliness that students begin by algebraic procedures, one may explore the investment on qualitative descriptions and the challenges this task entails. In addition, it is important to consider that students may never experience the need to develop such conceptual understanding of physics phenomena, as this type of knowledge may be rarely assessed through traditional instruments and textbook problems. It is reasonable to think that there are alternative reasons why students are unlikely engage in conceptual development, such as individual motivation and reduce background knowledge. Yet, I believe that teaching strategies, and with this the frequent use of well-structured problems as learning activities and through assessment instruments in university physics courses, contribute significantly to students lack of motivation for conceptual growth. Consequently, it is reasonable to think that university students would be reluctant to engage in such a demanding cognitive process if they are under the epistemological belief that good performance and grades come from appropriate algebraic procedures rather than conceptual understanding.

There is a great gap in knowledge to fully understand the implications and benefits from student groups generating problems, and solving ill-structured activities. In this study, I only analyzed 4 groups of the 26 distributed across the three sections. More in depth analysis may be required to identify whether sections and learning instruction have an effect over group performance and the processes these engage. Even though results are consistent across the analyzed student teams, I have not explored the sequence of processes these groups went through, which may respond to patterns associated with instructional strategies, in addition to individual and team level attributes. Recall that the Traditional section only worked on ill-structured problems once for the day of data collection, whereas the Treatment section used ill-structured problems every week, and where instructor emphasized the importance of assumptions, as well as encouraged social interaction for seeking out information. Accordingly, it may the case that a constant practice in groups helped students develop appropriate strategies for solving ill-structured problems in effective ways, whereas students lacking this experience may have spent more time dealing with defining steps to move forward. Because generating a problems was an activity only used on the day of data collection, it may be that groups from different sections experienced similar challenges related to the task, but differences for group coordination. This may be a consequence of the nature of generating problems as a learning activity, which demands higher levels of interdependency among group members relative to well-structured problems, and are likely to demand the sum of members' knowledge and experience (i.e., additive tasks) (Steiner, 1966).

5.2 Problem Characteristics

By exploring student-generated problems, I identified the key physics variables and attributes that characterize student conceptions and misconceptions of circular motion. In doing this, I show a novel way of assessing student generated problems, taking into account physics concepts and the different characteristics embedded in their problems. Such analysis may work for problem assessment, in alignment with creative perspectives, that is, taking into account novelty and effectiveness.

Students from all 3 sections showed adequate manipulation of the concepts for circular motion and applying them to creating a problem. The observed differences across sections on the use of variables for questions (e.g., uniform versus accelerated motion) may be consequence of instructors emphasizing and/or repeating physics variables and problems differently between sections. Variance in exposure to physics and related examples may have caused students from different sections to gain various levels of familiarity with the content, beyond the expected differences between individuals. The first difference I highlight is between the Mixed section addressing a majority of situations with no acceleration, compared to problems from the other two sections, which mainly focused on scenarios with constant acceleration. It is interesting that the combination of physics variables utilized for students from the Traditional and Treatment sections were a more complex combination of variables, but with no clear underlying structure (see Tables, Chapter 4). However, I was able to identify some consistency in the physics variables asked in the problems generated by students from the Mixed section, which mostly relied on highly related concepts (e.g., angular speed, period and frequency). Accordingly, instructor from the Mixed section may have used a higher frequency of questions, problems and examples addressing the mentioned set of concepts regarding circular motion in his/her instruction. In contrast, the different combinations of concepts used as questions by students from the Traditional and Treatment sections may indicate that the instructors in these sections may have utilized these concepts on a more balanced way. Getting access to data on instruction and the existence of different emphasis would constitute an improvement to understand the cause of the observed differences.

It is possible to perceive the variety of combinations of physics concepts as a reliable depiction of students' familiarity with such concepts, given two important pieces of evidence from the group processes and creativity. First, during discussion, groups are likely to select the right ideas to develop (Baruah and Paulus, 2008), and these ideas are likely to emerge faster from denser sections of the cognitive network (i.e., have higher value) than ideas proposed at later stages of group discussion, and perceived as less valuable (Johnson and D'Lauro, 2018). Taking this together, one may suggest that the combination of physics content introduce into the problems was decided and selected following the latter collective processes, where well-understood ideas are perceived as more valuable for the task, and therefore selected for their development. This claim supports the process of generating problems as valuable task for students to show their understanding and familiarity with physics concepts.

All sections had characteristics in their generated problems that included assumptions, algebraic transformations, and similar numbers of physics magnitudes asked for. The Traditional and Treatment sections wrote problems that showed higher *problem elaboration*. It is a surprise that the Mixed section had lower elaboration than the Treatment section. The learning conditions, problems and instructional guidance on how to solve problems engaged in during each section may have influenced students' motivation for creating problems with various levels of elaboration and complexity. For instance, the learning goal of the task (i.e., design a physics problem for secondary students) may have motivated students in the Traditional section to utilize characteristics from textbook problems that were in their repository of activities to design problems in an effective way. The Mixed section worked on ill-structured problems, but the instructor did not emphasize the importance of assumptions in the face of ill-structured activities, and were expected to generate problems as elaborated as the Treatment section. Consequently, highlighting the role of "assumption making" in problem solving sessions when students were tasked with creative tasks I believe had positive effects over students' expectations and motivation for generating problems, as suggested by the high *problem elaboration* found on problems from Treatment section, whose instructor engaged in such a positive narrative for creativity. The lower amount of elaboration observed in the Mixed section may also be partially explained by the suggested high redundancy of concepts used by the instructor, as students experienced reduce number of alternative scenarios where physics variables were displayed, and available for transfer into the problems they developed.

Limitations and areas of improvement relate to the speculation that assumptions as problem characteristics are not intentional, but caused by lack of knowledge and reduce experience on generating such learning questions. Let us remember that assumptions are defined as 'gaps' in knowledge that solvers needs to address before attempting to solve the problem. This 'gaps' showed the tendency to relate to particular characteristics of the problem, such as constant acceleration, or the position of the 'particle' that describes the circular motion, or other alternative conditions. Accordingly, one may assume these gaps are either intentional cognitive challenges for problem solvers, or caused by misconceptions over the nature of well-defined problems. In-depth analysis of alternative sources of error on students' problems, as well as mechanisms on how to optimize problem generation for appropriate knowledge development are goals for future research.

One pedagogical innovation for the use of student generated problems may be teams evaluating other's problems. This would be beneficial to identify sources of error, and is likely to motivate between-group discussions over ways to improve their respective activities, thus introducing elements of interdependency in the classroom, known as a key feature for collaboration (Johnson et al., 1986). A complementary use for such peer-peer evaluation of problems may be the assessment of creativity, that is, whether the generated activities are novel and effective for the purpose these were created (Runco and Jaeger, 2012; Sternberg, 2012). Here, students' perception of originality is likely a reflection of the unique set of physics problems solved throughout their student life.

Communicating the importance of such novelty when generating problems may motivate students into pursue alternative new ideas for their problem production, as observed in the high elaboration of problems from section Treatment. In addition, problem effectiveness, the second dimension for creativity, demands clear guidelines over what constitute an appropriate physics problem. If students where to generate mathematical problems, such as textbook activities, then the assessment of effectiveness needs to include explicit information over the well-defined nature of this type of problems in order for students to assess its quality. Consequently, educators might take advantage of this collective process of critique and assessment as a learning opportunity into the different characteristics to utilize for generating physics problems. Having students' assessments over the novelty and quality may be later introduced as an additional metric into the overall exploration of this problems taking in consideration the analysis method used on this study.

A big challenge of the method used to analyze student problems is that it relied on descriptive tools that are limited in finding differences and similarities based on observed frequency of concepts and different characteristics. The variable of *problem elaboration* is thought to be appropriate for aggregating the mentioned characteristics, however, by doing this I overlooked deeper structural characteristics that may have emerged due to teaching conditions. For instance, results on the set of physics concepts used by sections Traditional and Treatment do not seem to respect any apparent rationale, and further information is inaccessible through this analysis. I presume that the principle of independence, which is fundamental for standard statistical analysis, plays an important role in limiting further analysis as it enables the perception that each characteristic that is identified in a single problems is independent, and has no relationship with the other attributes observed in the same problem. However, it is likely that the use of contextual details, different types of information, as well as set of physics concepts into the construction of a problem is not grounded on the independence of the mentioned characteristics, but rather these may emerge from relational underlying connections. Accordingly, network analysis provides an interesting perspective for this purpose. With this, one would conceptualize sets of problems concepts and characteristics as nodes within the network of problems' attributes, with undirected links indicating the co-existence of these variables, and weights showing the number of times (i.e., frequency) these variables are observed together. This lens of analysis enables the measurement of network variables, such as centrality, accounting for a node's number of connections, with higher number of links indicating higher centrality. Such perspectives allow researchers and educators to detect communities of problem characteristics. As an example, Brewe et al. (2016) used network analysis for detecting communities of responses, that is, groups of choices that are likely to be selected together based on their correlations. This was conducted using responses to the Force Inventory, a multiple choice instrument designed to assess conceptual knowledge on force. Brewe et al. (2016) were able to identified three main modules (i.e., response communities) as the backbone of the network of possible responses, and therefore gain access to students' understandings based on the relatedness of their responses. This analysis allowed a deeper understanding about the patterns of responses students were likely to select, as a reflection of the scientific relations they developed throughout a physics course.

Finally, besides the descriptive nature of community detection, it is possible to test whether structural properties of the network of problem concepts and characteristics responds was either generated randomly, or do respond to underlying structural properties. For this purpose, one may use Exponential Random Graph Models (ERGM) (Borgatti et al., 2013), which enable researchers to predict the presence of a link between nodes based on structural properties and nodal attributes. Having the chance to explore different communities (i.e., networks) of concepts and characteristics, as well as the likelihood of these networks to be caused by structural properties would enable a more robust analysis and research over the features embedded on students' problems.

5.3 Social Network Analysis

As discussed in the literature review, network analysis affords researchers with methodological tools to explore classrooms and learning experience taking into account the relational nature of such cognitive and behavioral process (Grunspan et al., 2014). Consequently, I was able to identify such features, as well as differences and similarities across sections. For instance, being perceived as a good student is the only significant predictor of *indegree* centrality across all three sections, and therefore students are likely to direct their attention to recognized peers for information for solving the problem. This social process may be possible due to perceived hierarchies in terms of physics knowledge and skills for problem solving, and as McFarland et al. (2014) suggest, such mechanism facilitates distinction of status among students.

In general, the learning and teaching conditions enacted by instructors on the Traditional and Treatment sections allowed students to engage in similar levels of social interactions for information seeking, as indicated by the results on network centrality. The evidence suggest that both well- and ill-structured problems may have similar social implications for networking. However, taking into account the low social engagement observed by students from the Mixed section, one may say that such problem effects may be positive only for well-structured problems, as the learning conditions on Mixed section included ill-structured activities. Research suggest that in learning contexts governed by well-structured physics problems, individuals are likely to develop the epistemological belief that academic success in physics implies the enactment of novice problem solving strategies (e.g., bottoms-up) (Byun and Lee, 2014). Such belief may have motivated students to seek out information on multiple different sources within the classroom. Additionally, the well-structured nature of mathematical physics problems implies that the pieces of information needed for solving the problem are simple and easy to ask (e.g., equations and data to use). Network literature suggests that learning simple and codified information occurs through weak social ties (Granovetter, 1973; Hansen, 1999), as this requires less social investment compared to strong ties, which are preferred for more complex and non-codified knowledge. Because data was collected in the 7th week of the academic semester, one may argue that the patterns of interactions in each section had achieved appropriate stability (Bruun and Brewer, 2013), for when students solved the ill-structured problem of generating a physics problem. Finally, the similarities in social interaction between the Traditional and Treatment sections I believe was a consequence of different mechanisms. Because students in the Treatment group worked on ill-structured activities, I suggested that they did not engage in the processes of seeking information in the same way as students from the Traditional classroom (i.e., simple and codified knowledge). The lack of unique solutions in the Treatment learning context may have required them to either develop strong ties for accessing more complex ideas (e.g., deeper understanding of physics), or alternatively, presumed the need of simple knowledge for solving the problem, and consequently, accessed it through weak ties (Granovetter, 1973; Hansen, 1999). The higher elaboration of solutions observed on problems from Treatment section would suggest the former to be true (i.e., strong ties for complex ideas). In addition, the instructional strategy of guiding students to connect in the face of questions and difficulties is arguable a mechanisms that encourages both weak and strong ties depending the nature of the information needed.

Interestingly, being a central actor within the network of information seeking does not afford good *grades*. This evidence is redundant and observed for variables such as *outdegree*, *degree*, *betweenness* and *eigenvector* centrality. The directionality of the relationship between centrality and grades contradicts the research evidence found on other studies (Putnik et al., 2016; Bruun and Brewer, 2013; Grunspan et al., 2014). To understand this contradictory results, one could focus on the nature of the social networks mapped on this and other studies, and argue that the social processes these different systems entail as one of the reasons why I obtained such contradictory results. For instance, some studies in physics education have asked students to write down the names of their peers with whom they had meaningful interactions inside the classroom (Williams et al., 2017; Zwolak et al., 2017). Under such survey question, the students were likely to remember interactions with friends (Eagle et al., 2009), or useful interactions related to the learning goals of the session (Bruun and Brewer, 2013). Consequently, it may be reasonable to argue that not every friendship-based interaction would bring meaningful outcomes in the learning context, and therefore accounting for such relationship as a confounding variable may clean the evidence over the effects of meaningful interactions on performance. However, the analysis conducted on the mentioned studies do not include confounding variables such as friendship, perception of good students, or alternative metrics that might help isolate the effect of having multiple meaningful interactions in the classroom, and with whom. This scenario limits the understanding over the nature of the interactions that govern the social system, which may have masked the real effect of network centrality on academic performance.

In addition, the survey question used in this study was aimed to determine students' social engagement in the process of seeking out information in the classroom, where I provided the roster of students rather than having them report the names of their connections. Under these conditions, students may be also likely to report useful as well as friendship-based social interactions for information seeking, yet, these types of relationships may not necessarily overlap as the nature of the network does not account for the effectiveness of the social tie. That is, students may have interacted and reported ties with friends and others they do not consider friends for information for solving the problem, regardless of the meaningfulness of the interactions. Consequently and according to the negative coefficients of centrality over *physics grades*, students are either not capable of requesting appropriate information for solving physics problems due to ineffective communication, or it may be that engaging in such processes for information seeking is irrelevant in the learning context described here. If the former were true, this would be evidence for the need to engage students in the social processes linked to effective communication and collaboration. Yet, if the learning context were blind to social interactions and sharing information, then this would call for a reflection over the teaching and learning practices involved in university education, taking in consideration the importance of social processes in today's professional world and economy. Alternatively, it may be the case that students approximated effective social interactions, yet the actors reached lacked meaningful information to share, or rather provided misconceptions regarding the content and/or the goals of the task. Consequently, having nodes with reduced knowledge of the content is not an ideal scenario for students to engage in socialization of information for collective growth. This calls for remedial strategies that prepare subjects for proper learning before putting them in positions to collaborate.

A different reason for the negative effect of network centrality over performance may be attributed to the nature of the task and learning conditions students underwent on studies were positive effects have been found. For instance, in (Putnik et al., 2016), the network effects were measured in the context of a team-based learning project that students worked on throughout an entire semester, which involves interesting levels of interdependency (Johnson et al., 1986). Similar Modeling Instructions (Brewe et al.) is grounded on activities where students are required to discuss, reflect and build upon each other's understandings. These learning contexts show higher structure, longer duration, and presumably more instructional guidance than the learning scenarios covered in this study. Consequently, the latter features may be useful elements to utilize in future teaching and learning efforts involving ill-structured problems. When looking at the interaction between centrality and sections, the single effect of network structures is stable across multiple centrality measures in predicting *physics grades*, and with no differences found across sections. Yet, the models fitted for predicting *problem elaboration* would suggest that there are differences on the effects of centrality depending on the type of instruction. Consequently, the consistent negative effect of centrality for generating problems would depend on the type of instruction and problems students worked. Based on the interaction plots on Figure 17, one could notice the detrimental effects of centrality on the Mixed section, with clear positive effects for the Traditional section on *indegree* and *betweenness*, and less positive for *outdegree* and *degree*. The radical difference between Mixed and Traditional may be attributed to the combination of problems, and the need to invest on either strong and/or weak ties for accessing information. Based on these results, engaging on well and ill-structured problems without a narrative that highlights the importance of alternative ideas and creative processes (i.e., Mixed section) is likely to have limited students' motivation to engage on effective socialization of information for creating a highly elaborated problem, or due to the absence of appropriate ideas to share. Moreover, working on distinctive problems every other week may constitute an inconvenient learning strategy in the absence of appropriate guidance, as this may add confusion over the nature of ideas required for solving each problem, as well as the nature of the relationships students would need to develop in order to access it. In contrast, a consistent practice for well-structured problems is suggested to help students in transitioning from weak to strong social ties, under the assumption that the information shared for generating the problem is more complex than the one needed for well-structured activities. Further, an instruction motivated by ideas of creativity and social interaction afforded students from Treatment sections to experience effects of centrality to be less negative (e.g., *indegree* and *degree*) compared to Mixed section, and less positive (e.g., *outdegree* and *betweenness*) compared to Traditional. The negative effects may be attributed again to ineffective mechanism of communication and lack of clarity associated with the nature of the information needed for generating a problem, a phenomenon presumably moderated by the instructor every time he guided students to connect others for information.

To continue my interpretation of the network analysis, it is worth paying attention to the significant interaction between network constraint and course sections for predicting *physics grades*. Here, both the Traditional and Treatment show a positive relationship with grades, whereas for the Mixed section this relationship is negative. This evidence suggest that the social systems created under the Traditional and Treatment conditions take advantage of highly constrained networks, where subjects presumably engaged in deep analysis and reflection on ideas, or as Rhee and Leonardi (2003) called interrogation logic. Consequently, within such a cohesive network, it is easier to learn complex information, as well as to develop good ideas (Fleming et al., 2007). This process is evidence that the nature of well-structured (e.g., *physics grades*) problems does not benefit from the mechanism of creative combinations, but rather engaging in such efforts brings negative effects. This claim is supported by the negative coefficient on structural holes, a metric associated with access to non-redundant ties. Therefore, access to unique connections is related to inflow of novel ideas, which here does not afford better outcomes, likely because the well-bounded nature of the physics information for solving well-structured problems does not need novelty, but rather conventional knowledge. Further, the negative effect of constraint on the Mixed section suggests the opposite, where students benefit from connecting structural holes. Surprisingly, students on the Mixed section displayed higher network constraint relative to students from Traditional section. Consequently, not taking advantage of it for scoring higher grades may be due to ineffective communication for collaboration.

Moreover, and even though the models were not significant, maybe due to high standard error, constraint and structural holes show null effect for *problem elaboration* compared to the negative *physics grades*. In addition, I also observed differences in the signs of the regression coefficients for brokerage variables predicting *physics grades* and *problem elaboration*. For instance, such as *gatekeeper*, a positive predictor above and beyond sections for *problem elaboration*, but a negative predictor for *physics grades*. These results add interesting evidence to the contrasting nature of both types of performance, and regarding the nature of the learning objectives and the measurement instruments design for such purpose. Accordingly, generating problems may be close to benefiting from the social mechanism of combining information from multiple non-redundant ties (i.e., low network constrain) (Burt, 2004), provided students engage in effective mechanisms for information seeking in a context that rewards creativity, and in which subjects show appropriate knowledge and skills (Amabile, 1996). Contrary, well-structured physics problems which benefit from highly constrained networks. A mechanism that is likely to fit the contrasting nature of both activities is network oscillation proposed by (Burt, 2016). According to the author, individuals may oscillate between periods of intense socialization within a cohesive cluster, here appropriate for well-structured problems, and periods of intense brokerage for connecting ties with structural holes, found positive for ill-structured problems. This evidence sheds light over the influence of the learning conditions where individuals are required to perform creatively versus more conventional tasks, as well as the nature of the social processes that would be required for getting good outcomes on each task.

Finally, the interactions between *problem elaboration* scores and *degree*, *eigenvector* centrality and good student for predicting *physics grades* are consistent with the single effect of students' networks over *physics grades*. Accordingly, students who showed low social engagement for seeking out information, and had low levels (i.e., below the mean) on *degree* and *eigenvector* centrality are related to good *grades* when they scored high *problem elaboration*. This result is an additional evidence of the detrimental effect of socialization and seeking out information, presumably through ineffective mechanisms for obtaining good grades. Surprisingly, students who are not perceived as good students would get better grades if they score higher on *problem elaboration*. In simple words, according to my research, the complexity of generating a physics problems has negative effects on the students who enjoy the social recognition of being proficient in physics. The physics education tradition is grounded on mathematical physics problems (Byun and Lee, 2014; Chi et al., 1981; Kim and Pak, 2002; Larkin et al., 1980), and its consequent belief that a good physics performance is exhibited by solving well-structured problems has clearly encouraged students to recognize proficient others based on their ability to solve such math-based problems. Yet, this hierarchical position has not afforded perceived 'good students' with more opportunities for developing more elaborated problems as a proxy for creativity, as evidence throughout the multiple regression models predicting *problem elaboration*. As mentioned, generating an elaborated problem requires an alternative set of capabilities and skills than those required to solve well-structured problems. The literature on creativity provides a plausible explanation for why such a negative effect was observed consistently throughout this study. According to Sitar et al. (2016), both independent and collaborative oriented individuals are likely to be creative provided they show high self-efficacy and enjoyment respectively. Because well-structured problems are disjunctive tasks (Steiner, 1966) that can be solved without the need to collaborate, then one may presume that perceived good students are likely to solve such problems independently rather than collaboratively, and are capable of creative ideas as long as they show strong believes over their own abilities to perform accordingly. The lack of significance and sometimes negative coefficient of good student nomination over *problem elaboration* may suggest that perceived proficient students lack the required self-efficacy for creativity. Alternatively, students that do not enjoy such recognition of 'good students' may enjoy more collaboratively oriented tasks, like ill-structured problems, and therefore may be more capable of creating highly elaborated problems like the interaction would suggest.

5.4 Contributions

Based on the methodological approach taken for conducting this study, and the evidence that emerged from the results, here I present a brief description of the contributions to the field of physics education and social networks.

5.4.1 Physics Education

A first contribution emerges from the mixed methods utilized in this study, which would constitute a comprehensive approximation to the study of problem solving and collaboration. This methodological lens included an analysis of students' processes for solving problems, their solutions and the exploration of collaboration networks. With this, problem solving is perceived and conceptualized as a collective endeavour rather than the individualized approach constantly observed in the literature (Byun and Lee, 2014; Chi et al., 1981; Docktor et al., 2015; Larkin et al., 1980). Studies in PER have paid attention to students' discussion for learning and solving diverse types of activities (Heller and Hollabaugh, 1992; Harlow et al., 2016; Leinonen et al., 2017), as well as used SNA to explore the relationship between collaboration and performance (Brewe et al.; Bruun and Brewer, 2013; Bruun, 2014), and retention (Zwolak et al., 2018, 2017). Yet, these methods have not been combined to explore the social dimensions that influence students' outcomes.

This multidimensional lens of analysis (i.e., processes, collaboration and problem outcomes) would be particularly useful in the face of additive learning activities (Steiner, 1966) that include high levels of interdependency (Johnson et al., 1986), such as ill-structured problems. Even though this method might also be valuable for the analysis of well-structured problems, the uniqueness of solutions eliminates or diminishes the exploration of problems' outcomes, thus leaving the analysis to the exclusive exploration of group-level processes and collaborative networks. Another limitation with well-structured problems might be the lack of collaboration observed in groups addressing such learning activities, given these are characterized by low levels of interdependency, and therefore tend to be solved by the most dominant members without the need to rely on a collective construction of ideas (Heller et al., 1992). This might limit the information observed at group-level, as in the context of math-based problems, students are likely to engage in bottom-top strategies (Meltzer, 2005; Shing, 2008), and consequently, discussion would be focus on math procedures in detriment of physics-related ideas. In addition, because the analysis of problem solutions relays on emergent characteristics, this method would facilitate the analysis over the full spectrum of forms that ill-structure problems (i.e., real-world problems) might take.

A second contribution relates to the understanding of proficiency in physics education. The multiple regression models suggested that perceptions of proficiency were associated with abilities to solve well-structured problems, and presumably, grounded on math-oriented skills rather than a deep comprehension of physics knowledge. This is evidenced in the positive coefficient observed for the variable good students on the models for physics grades, but where the effect of this perception of skills had a null effect over the variable that summarized the performance on ill-structured problems.

This is true even for students on the Treatment and Mixed sections, who dedicated their time to ill-structured problems, and consequently, one might have expected them to expand their understanding over their perception of proficiency towards skills associated with idea-generation and/or collaboration. This evidence motivates a reflection over the characteristics and contextual conditions that enable such restricted perception of proficiency in physics education.

A tradition of individualized testing in physics education, specially grounded on the use of math-based problems might be the responsible for a limited perception of proficiency. Here, the social context where subjects are engaging in learning must value a broader and more comprehensive set of skills, like communication, idea-generation, decision-making, and content knowledge among others. However, accomplishing this would require not only new teaching strategies, but assessment methods designed to highlight these set of integral skills. Any instructional endeavour oriented to expand the skills and information students are expected to develop must be joined by assessment instruments that mirror such principles. If this condition is not met, subjects are likely to perceive the distance between these two elements (i.e., instruction and assessment), and as response, they might focus on what would afford them good performance instead of higher value competencies.

5.4.2 Social Network

The social network literature cited in this work is grounded on the assumption that social ties enable the access to information. That is, individuals would learn information held by the actors connected through social relationships of different nature. This conceptualization of social learning assumes that actors have relevant and appropriate levels of knowledge for others to take advantage of. This process motivates the assumption that every member in the network is knowledgeable enough, first, to provide valuable learning opportunities for their connections, and second, for these individuals to be capable of assessing the quality of the information to be learned as relevant for their unique purpose. The evidence found on the social network literature tends to emerge from professional organizations where actors presumably have relevant knowledge to share, and consequently, having multiple different ties that spanned structural holes, as well as membership in a constrained network are likely to enable better learning and the emergence of good ideas (Burt, 2004; Burt and Merluzzi, 2016; Borgatti and Cross, 2003; Reagans and McEvily, 2003; Fleming et al., 2007).

An additional assumption implies that subjects are able to engage on appropriate communication and social processes for collaboration, which would enable them access to the pieces of information needed for the particular tasks. That is, so far the network literature revised here has not paid explicit attention to the quality of these social interactions. In its defense, the professional settings might push one to think that actors on these contexts have developed the competencies for socialization, presumably after years of experience. For this reason tenure is often used as a control variable (Ibarra, 1993; Leonardi and Bailey, 2017; Reagans and McEvily, 2003; Rhee and Leonardi, 2003), but with null of negative effects over performance and good ideas. This variable may account for knowledge expertise and communication skills. In addition, tie strength is often used as independent variable, and has shown positive effects over performance (Reagans and McEvily, 2003; Sosa, 2011). The strength of a social tie may be understood as a fair approximation towards effective interaction and communication, as stronger ties are observed between subjects who have invested time and energy into the relationship, and therefore, have built appropriate mechanisms for communicating ideas.

In studies on networks in education, the survey questions have shown the tendency to ask students for meaningful interactions, but with not metrics related to students' collaborative abilities (Putnik et al., 2016; Bruun and Brewer, 2013; Zwolak et al., 2018). Furthermore, and based on the evidence found on this study, the assumption that network actors have relevant and appropriate information to share with others may not be invariant across different social contexts. In the particular case of education, one may think of a temporal distance between facilitating new information into the class by the instructor, learning it, and then share it through social ties with other members of the course. The disconnection between the process of developing appropriate understandings of the content, and engaging in social interactions for accessing diverse ideas related to the content is evidence of the negative effects of centrality over performance on both types of problems, but more evident on well-structured activities. Under such conditions, it is likely that students would engage on ineffective interactions due to lack of basic understandings.

5.4.3 Limitations and Future Recommendations

I recognize the limitations of this study associated with the reduced sample size, and the lack of alternative variables that would have strengthened the analysis of students' responses and social experience. Further control and observation over instructional strategies would also facilitate a deeper understanding of the nature of the social system generated on each academic section. In addition, short term activities like the problem design for a single session might discourage interdependency and continuous collaboration among students. Consequently, future pedagogical innovations should include higher level of structure, with explicit learning goals at the individual and group levels, similar to project-based instruction used in Putnik et al. (2016). An important dimension for improvement consists of understanding the different ways in which students collaborate and gain access to information from their peers. Such effort might support the interpretation that students engaged in ineffective forms of communication when solving different types of activities, which would lead to recommendations over the importance of appropriate strategies for social capital depending on the nature of the task. Additional evidence of students' strategies for social connection may support the need to introduce pedagogical innovations that respond to creativity and collaboration in university education. However, and in coherence with the dichotomy between independent versus collaborative oriented students (Sitar et al., 2016), having access to whether students are comfortable in the face of collaboration and social interactions would add valuable information to understand the appropriateness of pedagogies grounded on socialization of information, as well as to think about the roles independent students are likely to meet within such learning context.

Based on these results, educators must be cautious in implementing teaching strategies grounded on principles of collaboration and interdependency. Using such principles demands intense attention on students' interactions, and appropriate guidance over effective strategies for collaboration and communication of information. In addition, introducing ill-structured problems in education brings positive learning outcomes and interesting opportunities for creative thinking, yet, this is true when instructors guide the solving process and motivate students to engage in the appropriate cognitive demands these problems entail. The latter is supported by the significant difference between the Treatment and Traditional sections for predicting grades. In addition, having students develop appropriate content knowledge before attempting to introduce activities that require intense knowledge transfer may induce richer dialogues. The course where I conducted this study divided the curriculum into weekly learning sessions that included two sessions of lecture and one session designed for solve problems. Accordingly, each week, instructors addressed new content (e.g., circular motion), which they introduced and explained in two lecture sessions. They then administered either well or ill-structured problems to assess students' knowledge on the content presented during lectures. The curriculum overloaded with content knowledge that students were expected to acquire caused time restrictions, which were particularly challenging in courses with multiple sections, each with unique assessment instruments. In order to respond and adapt to such limitations, one could argue in favor of curriculum flexibility, that is, a course program with less volume of information that facilitates knowledge development, as well as time for designing spaces where students could engage in creative thinking and collaboration. Consequently, future efforts and recommendations should be made on the course structure, and most importantly on new mechanism for assessing students' knowledge development and skills. The contrasting evidence on the predictors that enable good *grades* and *problem elaboration* should call for an intense reflection over the learning goals and beliefs physics educators are perpetuating through individual assessments based on textbook problems.

Finally, as far as the literature reviewed and the evidence, there are no instructional strategies for students to become aware of the importance of their social ties, nor on how to take control over them. For instance, I presume that most students may lack the skills to transition from peripheral towards central positions of the classroom network, and in the opposite direction if the activity demands it. This may include the importance of brokering knowledge and cohesive clusters, particularly if the learning context emphasize and values knowledge diversity. Moreover, it might be worth exploring the extent to which instruction design for social networks could encourage (or discourage) the development of appropriate social competencies for optimal adaptation into different social contexts, as well as its effects over students' perceptions and values of collaboration. Both possible research objectives reflect a shift in the focus of formal education, from content-oriented to collaboration-oriented. Again, the latter stresses the importance of social competencies as the means through which knowledge building is likely to occur, but under appropriate guidance and standards.

5.4.4 Conclusions

The study conducted included analysis of group processes, student generated problems, and students' social networks. First, using ill-structured problems has shown to provide interesting opportunities for students to discuss multiple ideas and issues, particularly if these activities consist on students generating unique learning activities. The learning opportunities created by the ideas needed for generating problems constitutes an opportunity for students to engage in decision making and problem solving strategies. Both types of processes align with what experts are likely to do when facing real-world problems, and thus may be reasonable to think that continues practice would encourage students to adopt expert-like strategies for solving problems.

In addition, I was able to identify the different set of physics variables and characteristics utilized for generating their problems. In doing this, I proposed a new mechanism to assess the value of students' problems, taking in consideration not only scientific correctness (e.g., correct use of physics variables for a well-defined problem), but also non-scientific elements, such as contextual details, wording, number of questions, type of data introduced into the problem, among others. Accounting for the scientific and non-scientific problem characteristics allowed me to explore the level of elaboration and challenges embedded on each activity. The positive difference obtained in favor of the Treatment versus Mixed sections support the importance of engaging in creative tasks within a context that rewards and values such effort.

Finally, having students solve ill-structured problems within a learning environment that highlights the importance of creativity and socialization of information (i.e., Treatment condition) is likely to make students have better grades compared to traditional classrooms. Further, evidence suggest that socialization of information is not important for getting good physics grades, or solve well-structured problems, regardless the nature of the learning environments studied here. Moreover, well and ill-structured problems respond positively to different social structures, and therefore, social positions that afford good grades may be detrimental for solving ill-structured problems, where the learning environment plays an important role in enabling appropriate knowledge distribution across members, as well as effective communication.

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